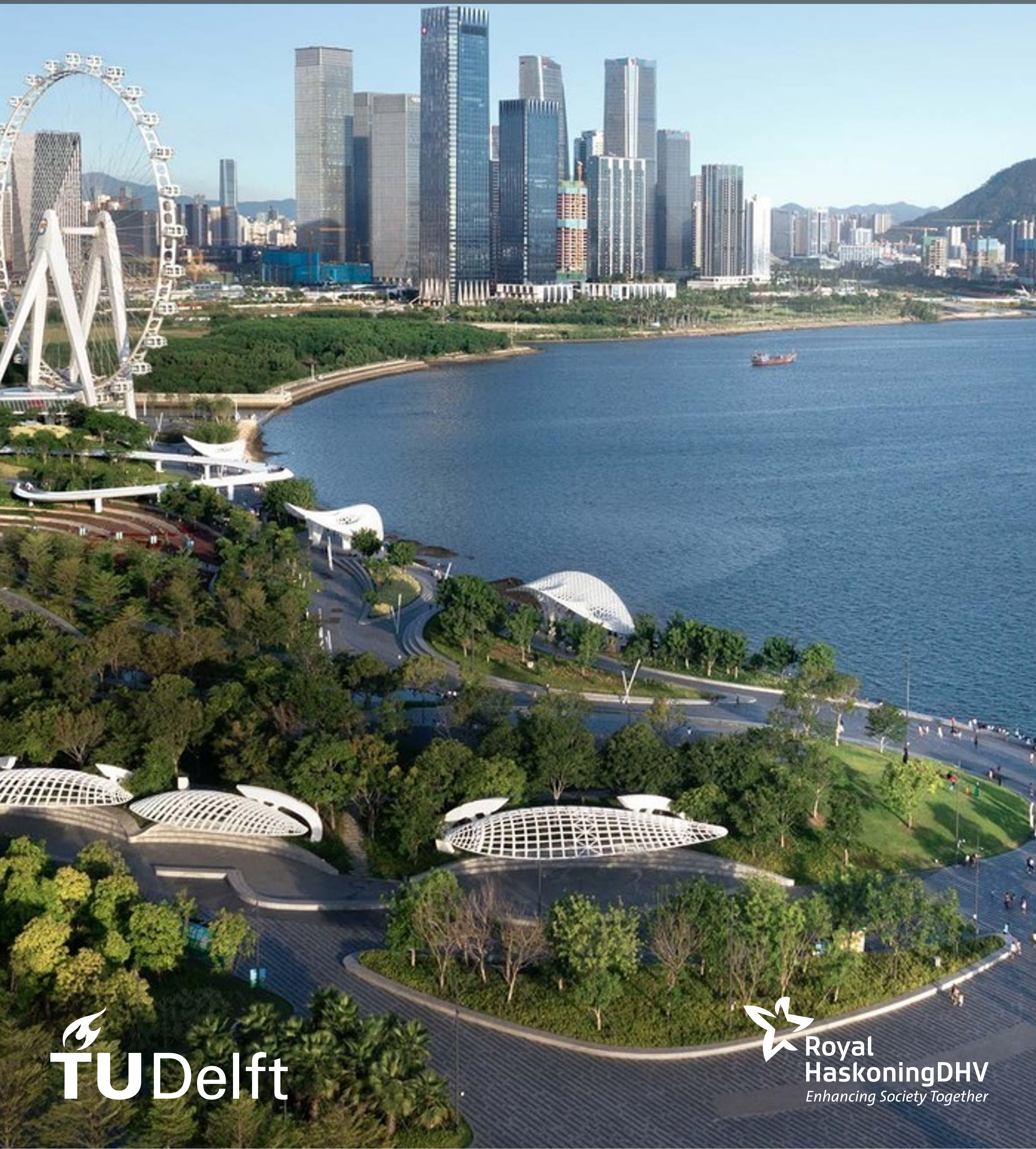
The economic evaluation of adaptive pathways for flood risk reduction strategies

M. A. Montijn



The economic evaluation of adaptive pathways for flood risk reduction strategies

by

M. A. Montijn

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Preface

Over the past few months, I have delved into the world of evaluating flood risk reduction strategies, gaining valuable insight into the challenges decision-makers are currently facing. I am grateful for the opportunity to explore such a relevant and pressing topic. The impact of climate change, that comes with great uncertainty ranges, is putting immense pressure on our current systems and adaptation has become unavoidable. Developing the optimal strategy towards resilience is crucial.

Reflecting on my personal journey through this thesis, the term ”resilience” is relevant as well. While it is not often applied as a personal quality, ’the ability to recover or bounce back from adversity or difficult situations’ is definitely something I have learned in the past months. Writing a thesis is challenging on its own, which was intensified by setbacks of my concussion. Nonetheless, I am more than content with the research and grateful for the personal growth that came with the experience.

This thesis would not have been a success without the help of a select group of people. First and foremost, I want to thank my graduation committee for supporting and guiding me through this process. Specifically, I would like to thank Matthijs Kok for his valuable advice during our meetings. These meetings not only covered the content but, also the soft skills that come with writing a thesis and the (life) lessons that followed were discussed. Next, I want to thank Martine Rutten for her feedback and specifically for her critical view of the thesis outline. Her comments really supported the structure and readability of this report. Then I would like to thank Cong Mai Van for this sharp comments during the meetings. His refreshing remarks inspired me and elevated the level of my research.
Next, I want to thank Matthijs Bos, my daily supervisor, from Royal HaskoningDHV, for providing me with valuable insights into the practicalities of flood risk strategies. I especially appreciate the opportunity to visit Singapore. This was an invaluable and unique experience that gave me insights into Singapore’s major project to prepare for future climate change. Additionally, I want to thank my colleague Lars de Ruig, who spend much time on helping me with scoping the research and enhancing the scientific level of the study.

I also want to express my gratitude to my parents and grandfather for their unconditional support and encouragement throughout this journey. They remained (or pretended well) interested in my doubts, frustrations or coding struggles. I am especially grateful for the pride my grandfather expressed when I would graduate and earn my engineering title. This gave me an extra boost of motivation. Finally, I want to thank Stijn for continuously nourishing my mood with his endless optimism, belief, and thoughtful coffee treats.

Writing this thesis has been a valuable experience for me, both academically and personally.
Enjoy reading.

M.A. (Maria) Montijn
Amsterdam, June 2023

Summary

The IPCC reports show that the scientific understanding of climate change and its consequences have increased, and mitigation measures alone are no longer sufficient to prevent its impact. The financial needs for adaptation measures are estimated to be significant, particularly in developing countries. The projected annual needs have almost quadrupled in the last 10 years and are expected to reach \$160-\$340 billion/year in 2030 and up to \$315-\$565 billion/year in 2050 UNEP (2020).

The sea level rise (SLR) is considered to be one of the most severe threats of climate change. Even with maximum response efforts, the risks associated with SLR are likely to remain moderate to high. The uncertain nature of SLR adds to the challenge of allocating the available financial resources efficiently, as there is a likelihood of unnecessary investments or extensive damages in case the climate scenario turns out to be different from expected.

Adaptive pathway planning is considered as a promising approach to develop flood risk reduction strategies that can adapt to changing circumstances. The use of adaptive pathways enables decision-making over time in response to how the future unfolds. As the stakes are high, it is important that the best strategy is followed, which requires an evaluation method that acknowledges all the strengths of the strategies. Analysis of existing methods showed that to capture the value of adaptive pathways, it is important to consider uncertainty, evaluation metrics, and the value of time. Uncertainty needs to be incorporated in the evaluation of a strategy, either through a scenario-based approach or a sampling technique. Multiple evaluation metrics should be used to obtain a deeper understanding of the performance of a strategy which supports decision-making. The value of time lies in the ability to reassess and reevaluate with newly obtained data that becomes available over time, which connects with the premise of adaptive planning. Creating decision moments in the strategy is essential to achieve different levels of adaptability, and find the right balance between flexibility and costs. Overall, by considering these focus points, a new framework for evaluating flood risk strategies was established.

The framework utilizes Monte Carlo analysis to account for uncertainty and samples futures from a single set of uncertainty distributions. Besides the traditional economic metrics net present value (NPV) and Benefit-Cost Ratio (BCR), the Equivalent Annual Costs (EAC), Probability of Loss (PoL) and Coefficient of Variation (CV) were included to support the decision-making process. The CV was found to be less useful as it did not provide useful insights. The SLR was assigned as a variable that experiences a reduced uncertainty when times passes. It is formulated as such that if the range of the projection of SLR for 2100 is considered now in 2023, it will be bigger than when it is considered in 2050. This extra knowledge is used in the decision of the new investment at the decision moment. Decision moments are the points in time in which the current measure no longer suffices and new measures are required. By varying in envisioned lifetimes of measures, and measures with different lead times, different levels of adaptability can be accomplished. Furthermore, from Real Option Analysis, the concept of formulating and creating extra flexibility in terms of options was retrieved. This was formulated in one of the strategies, in which a flexibility premium was included. It entails higher costs upfront to achieve lower costs for possible future investments. The performance for this strategy increased when the probability on a high SLR-scenario increased.

The developed framework was created in a Python environment and then tested for 7 different strategies on a conceptual case study. Additionally, 4 sensitivity tests were conducted to assess the framework's robustness. The results demonstrated that the framework effectively captures the impact of uncertainty and the value of time. Although these features did not significantly influence the results, the framework provides a good foundation for further studies. It should be noted that not all strengths of adaptive pathway planning, such as preventing future lock-ins, could be quantified in this analysis.

Furthermore, the tested strategies were simplified and did not address challenges like varying lead times of measures that arise in adaptive planning. The study highlighted that various factors influence the performance of a strategy, such as the risk profile and the discount factor.

Future research should focus on refining and validating the framework through real-world and more complex case studies, including the evaluation of adaptive pathways' performance. Additionally, investigations should extend beyond SLR, considering different stochastic variables to assess if they can benefit from reduced uncertainty over time. Furthermore, it is crucial to incorporate a comprehensive assessment of the entire flood system, including both pluvial and fluvial flood risks. Once established, the refined framework holds good potential as a valuable evaluation tool, enabling the justification and comparison of static and robust strategies against more flexible adaptive strategies.

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Acronyms

ATP Adaptation Tipping Point. 18

BCR Benefit-Cost Ratio. iii

CBA Cost-Benefit Analysis. 2, 11

CV Coefficient of Variation. iii, 31, 48

DAPP Dynamic Adaptive Policy Pathways. 2, 6, 8

DMDU Decion-Making under Deep Uncertainty. 6, 8

EAC Equivalent Annual Costs. iii, 24

ESL extreme sea level. 17

GDP gross domestic product. 7

GHG greenhouse gas. 6, 7

GMSL global mean sea level. 14

IPCC International Panel of Climate Change. vii, 1, 2, 7, 14, 15, 27

MC Monte-Carlo. 10

NPV net present value. iii, 24, 31

O&M Operations and Maintenance. 17, 24

PoL Probability of Loss. iii, 31, 32

RCP representative concentration pathway. viii, 1, 2, 17

RDM Robust Decision Making. 2, 3

ROA Real Option Analysis. 2, 3, 11

SLR sea level rise. vii, viii, 1, 2, 14, 15, 17, 18

SSP shared socioeconomic pathway. viii, 1, 2

1 Introduction

The consequences of climate change are becoming increasingly apparent, with droughts, extreme rainfall events, and severe coastal flooding occurring with greater frequency and magnitude. These events pose a significant threat to communities around the world, as demonstrated by recent disasters like the unprecedented floods in Pakistan (Magramo, 2022), the worst drought in 500 years in Europe (Toreti et al., 2022), and Hurricane Ivan which is recorded to be the deadliest hurricane in Florida since 1935 due to damage caused by coastal flooding and wind (Finch, 2022).

In the past decade, the scientific understanding of climate change and the consequences has increased. As a result, the future damage expectations have been adjusted upward. In the early stages of research into climate change, the International Panel of Climate Change (IPCC) report of 1990 concluded 'unequivocal detection of the enhanced greenhouse effect from observation is not likely for a decade or more' (Houghton et al., 1990). Whereas in 2007 the IPCC report stated: 'unequivocally, the climate is warming' (Solomon et al., 2007) and in the 2021 IPCC report scientists stated: 'scientific evidence is unequivocal: climate change is a threat to human well-being and the health of the planet' (Pörtner et al., 2022). In the same report, researchers specifically convey the urgency of adapting to climate change. Mitigation measures such as reducing the emission of greenhouses gasses will no longer be enough to prevent the impact of already occurring consequences of global warming (von Braun et al., 2022). Therefore, significant investments in adaptation measures are necessary to become more resilient against the consequences of climate change.

Consequently, the need for financial resources is increasing, especially in developing countries. In 2010 the World Bank estimated that by 2050 the financial adaptation needs of 76 developing countries would be \$70-100 billion/ year (Margulis et al., 2010).

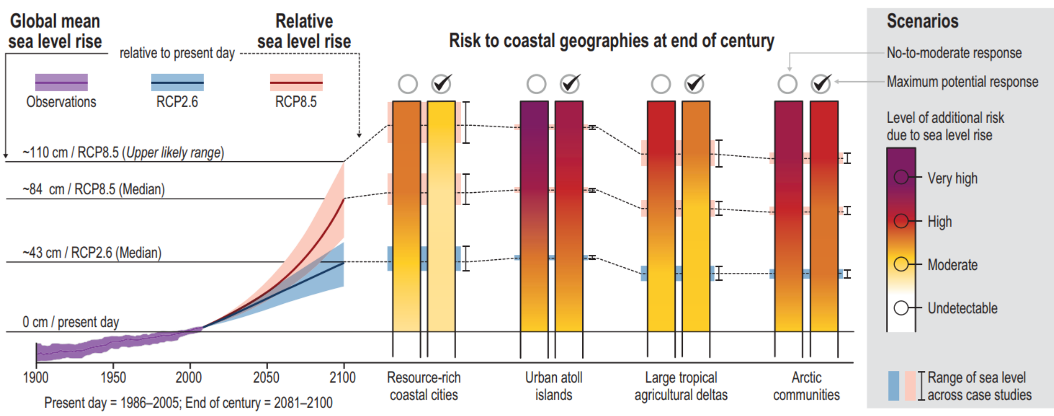


Figure 1.1: 'No to moderate response' in this figure represents a business-as-usual scenario in which no extra adaptation measures are implemented compared to the current level of effort. 'Maximum potential response' describes the opposite situation in which an ambitious plan is executed, including both incremental and transformational adaptation, which implies significant extra effort than today's plan.

In 2020 however, only 10 years later, the Annual Adaptation Gap report projected that the annual adaptation needs for these countries will reach $160-$340 billion/year in 2030 and up to $315-$565 billion / year in 2050 (UNEP, 2020). The projections have more than quadrupled. The UN Secretary-General António Guterres mentioned that the support of the developed countries stands at less than one-tenth of the amount that the developing world needs ("Guterres", 2022).

Sea level rise (SLR) is seen as one of the most severe threats of climate change. If no adequate actions are taken quickly, some of the world's largest cities are likely to be underwater by the end of 2100 (Pachauri & Meyer, 2014). The IPCC has forecast that by 2050, around one billion people will be living in low-lying coastal areas, compared to the 680,000 million who live there today (Pörtner et al., 2022). Even with maximum response efforts, the risks associated with SLR are likely to remain moderate to high, as shown in Figure 1.1. It illustrates the additional risk posed by SLR for different geographies.

Adapting to climate change is an increasingly pressing issue, as evidenced by the strong increase in expected costs over the last decade. Limited financial resources pose a significant challenge to governments and organizations seeking to implement effective flood risk reduction strategies. Compounding this challenge is the uncertain nature of climate change, which introduces a range of uncertainties into planning and decision-making processes. Therefore, allocating the available financial asset in the most efficient manner is paramount. The consequence of climate change uncertainty is that there is a likelihood that in case the climate scenario turns out to be milder than expected, unnecessary investments will be made. Contrarily, if the climate change impacts turn out to be more severe than expected, there are chances of extensive damages.

1.1. Problem formulation & Scientific Relevance

In order to develop effective flood risk reduction strategies that can adapt to changing circumstances, planning approaches that incorporate adaptability and flexibility are essential (Munene et al., 2018). To accommodate flexibility into decision-making and account for the evolving nature of flood risk, the application of 'adaptation pathways' have been identified as a promising approach (Werners et al., 2021). Adaptive pathway planning enables decision-making over time, in response to how the future unfolds. Haasnoot, Kwakkel, Walker, and Ter Maat (2013) created the Dynamic Adaptive Policy Pathways (DAPP) method in which adaptive pathways are used to develop plans that are subject to uncertainty. Figure 1.2 shows a schematic overview of the pathway map, a feature of the DAPP approach. It shows the available actions and how different pathways can be chosen.

Several methods exist to economically evaluate adaptive strategies. Some of the commonly used or closely related methods are; Cost-Benefit Analysis (CBA), Cost-Effectiveness Analysis (CEA), Real Option Analysis (ROA) and Robust Decision Making (RDM) (Haasnoot, van Aalst, et al., 2020). In pathways research, these methods are used to calculate the costs of individual actions and evaluate the benefits of pathways over a given time horizon and (multiple) scenario(s).

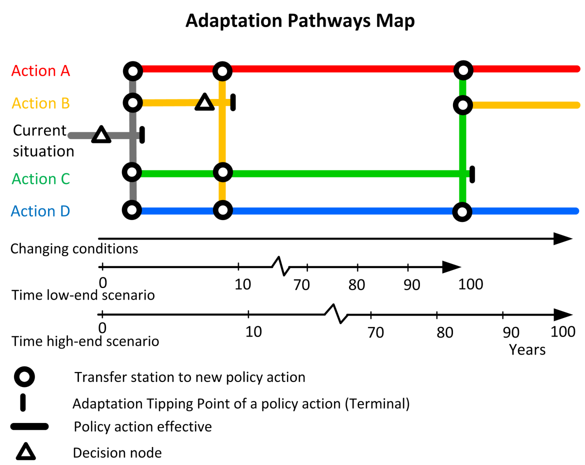


Figure 1.2: illustration of the Dynamic Adaptive Policy Pathway (DAPP) method. Different pathways are schematized that illustrate the sequence of actions that can be followed to achieve pre-formulated end goal.

The traditional method for evaluating strategies are the CBA or CEA, and are easy to implement and communicate. These methods, that evaluate the economic performance by discounting future cashflows, tend to focus on short-term returns on investment, which is often accomplished by using a short-time horizon: 20-30 years. But a short time frame mismatches the measure's lifespan and therefore the long-term benefits to a project area (Publishing, 2013). Besides, CBAs and CEA's are often focussed on a single measure, instead of a sequence of measures. Feinstein and Lander (2002) argue that a CBA is not appropriate when making investment decisions in case of an uncertain future, as it is not able to take managerial and policy flexibility in to consideration. The study of de Ruig (2020) on the other hand, showed that a CBA is able to include uncertainty in a study for an adaptation project in Los Angeles. The moment the new measure was implemented was determined by stochastic variables. The same method was applied by the thesis of Trommelen (2022). The recommendation that followed from this research is to incorporate the flexibility in the economic assessment that would enable alterations in the type and/or height of subsequent measures for conditions different from assumed.

An evaluation method that specifically addresses future uncertainty is ROA and is considered to capture the value of flexibility (Buurman & Babovic, 2016). At every moment, the option to invest or not to invest is evaluated. The value op options of taking measures later or now are valued. However, the downside of ROA is that it is complex to perform as many uncertainties need to be quantified, integrated and discretized in scenarios, as showed by J. M. Kind et al. (2018).

Another method that includes future uncertainty is RDM. The objective of RDM is to define possible options for adaptation strategies that are expected to perform well over a wide range of futures. Or, in other words, show 'robust' behaviour. With robustness as main objective, economic optimization becomes less important. RDM experiences the same challenge as ROA, namely, the potential lack of quantitative probabilistic data, (Vavatsikos et al., 2022).

In the most recent study of Haasnoot, Kwadijk, et al. (2020), the above-mentioned limitations of the various methods were noted as well. The research developed an economic framework in which a range of potential futures are considered. It then evaluates the costs and benefits of each pathway under each scenario. The most effective pathway will depend on the climate and social-economic scenario. However, in this evaluation method, the possibility to include updated knowledge what becomes available when time passes, is absent. Furthermore, although the best pathway for each scenario is defined, it does not make the choice for the pathway straightforward as it all comes down to deciding on which SLR-scenario to assume.

So to summarize, various methods to formulate and evaluate flood risk strategies have been tested in the past decade. However, each method has its strengths but also its limitations. The option to reevaluate and reassess is one of the advantages of adaptive pathway planning. At this moment, no method was found that evaluates strategies under uncertain conditions, and include the premise of 'updated knowledge' that become available when time passes. In Figure 1.3, the process of ongoing reduction of uncertainty is schematized. Besides, no literature was found in which static (the opposite of adaptive) strategy were compared with adaptive strategies, for either a real case study or for different conditions. Furthermore, if no adequate evaluation method exists, it also not possible to validate the positive and promising expectations about adaptive pathway planning. This research has been set up with the aim to fill in gaps that were identified in recent studies and to contribute to enhancement of economic evaluation of adaptive pathways.

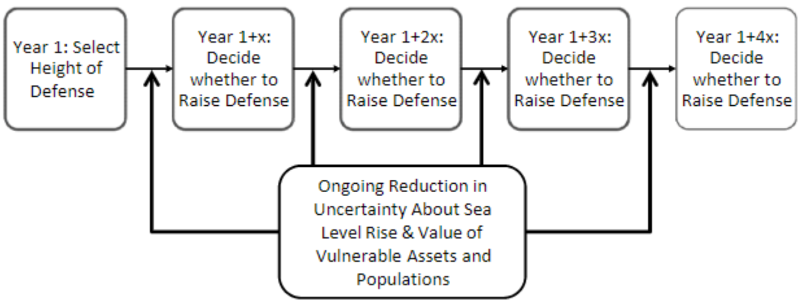


Figure 1.3: Example schematization of sequential decision-making. At every new decision moment, one can profit from reduction in uncertainty about factor like SLR and value of vulnerable assets. (Linquiti & Vonortas, 2012)

1.2. Research Objective

The aim of this research was to develop an evaluation method that supports decision makers with the comparison between static and adaptive strategies. This study aimed to quantify the added value of adaptive pathways, which involves incorporating the value of flexibility. In this way, the choice for a static and robust strategy or the flexible strategy can be justified. The framework should function at a conceptual level, which means that the research focussed more on the methods that are applied than on the exactness of the flood risk reduction strategy. The objectives are listed below.

The evaluation method should...

- .. be able to include uncertainty,
- .. include the value of flexibility,
- and provide insights that enable thorough comparison between static and adaptive strategies.

To accomplish this objective, the main research question has been formulated as follows:

> ***How can flexibility be integrated in the economic appraisal of adaptive pathway planning with uncertain future flood risk conditions?***

In order to derive the answer to the main research question, the research question has been broken down into 4 sub-research questions (SRQ) to guide the process. These are formulated as follows:

1. **How can the traditional evaluation method be extended to enable capturing the value of adaptive pathway planning?**
   The essential first step of the research is to investigate how the traditional evaluation method can be extended in order to capture the value of adaptive pathways. This includes reviewing the traditional evaluation method, but also previously performed research in valuing flexibility.

2. **In adaptive planning, what variables will experience a reduced uncertainty that will benefit the outcome?**
   Many variables influence the economic performance of a flood risk reduction strategy. Most of these factors, like the SLR-rate, are subject to uncertainty. One of the premises of adaptive planning is that there is a possibility to 'update' the earlier used data as more knowledge becomes available when time passes. This can result in a reduced uncertainty, which can lead to improved decision-making. In contrast, to static planning, in which the projections don't change. If and how this uncertainty changes depends on the variable.

3. **How could a framework be formulated to evaluate static and adaptive flood risk reduction strategies?**
   A framework will be developed which is then tested for a conceptual case study. The framework should enable a more thorough insight on the behaviour of static versus the adaptive strategies.

4. **What are the factors that influence the robustness of the framework?** The framework, which contains assumptions, should work for every case study. It is important to evaluate which factors influence the robustness of the framework.

1.3. Scope

To ensure an in-depth research and focus on the formulated objectives, a scope for the research is defined. This involves this following:

- The adaptive pathway planning method is only tested for long-term (+100 years) flood risk reduction strategies for coastal areas.
- Only coastal flooding is incorporated in the analysis, pluvial or fluvial flooding are therefore out of scope.
- In the risk assessment, only economic risk is evaluated. This implies that individual and societal risk are not included (Vrijling, 1984).

- As evaluation criteria for the pathways, only quantitative economic performance parameters are taken into consideration. This is done to refrain from subjectivity as much as possible.
- The research aims to provide and analyse the developed framework on a conceptual level. Not all possible measures or possible (climate) conditions will be evaluated.

1.4. Methodology and Outline

The first part of the research focussed on gaining knowledge on how to compare static and adaptive strategies. The answering of the first two sub-research questions (SRQ1 & SRQ2) were based on a literature study in Chapter 3. The findings from this review were then used to design the framework which can be used to evaluate different flood risk reduction strategies in which flexibility is taken in to consideration. Once the evaluation method is defined in Chapter 4, the framework will be tested on a conceptual case study, described in Chapter 5. After this conceptual case study, SRQ3 was answered. After the results from the conceptual case study were analysed, sensitivity tests were performed. The sensitivity test enabled answering SRQ4. In Chapter 6 the results from the preceding chapters are reflected against the limitations of the executed method. Next, in Chapter 7, all sub-research questions were answered, and eventually the main research question is answered and conclusions were drawn. Finally, recommendations are given for improving or extending the performed research. Figure 1.4 gives a schematic overview of the outline of this research report.

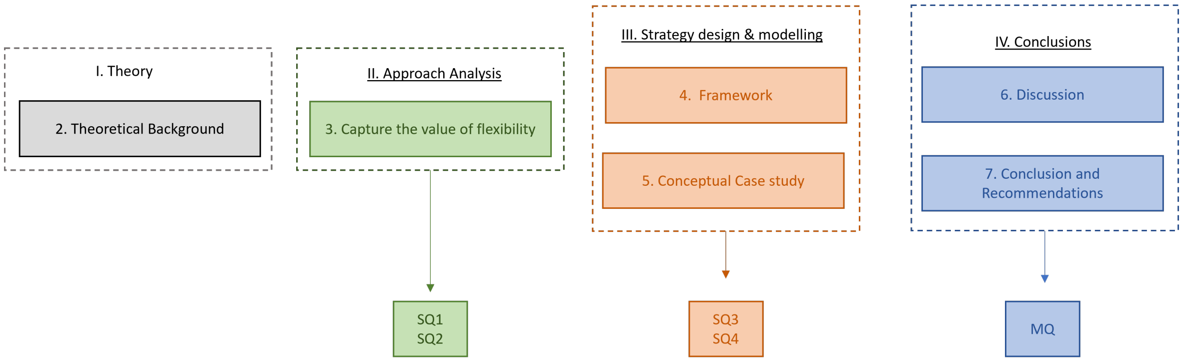


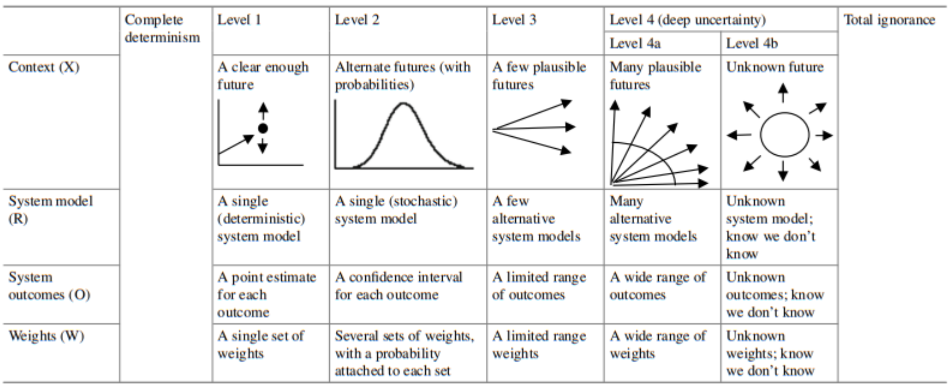
Figure 1.4: Overview of the report outline of this research. The chapters are listed and the link with the research questions are visualized.

2
Theoretical Background

This chapter provides the general background theory that forms the basis of this research. Section 2.1 provides a general overview of different levels of uncertainty which is relevant for long term flood risk reduction strategies. These unavoidable uncertainties are fundamental to the development of Decion-Making under Deep Uncertainty (DMDU) methods. An in-depth outline of the adaptive pathway planning method is given in Section 2.3, in which the DAPP approached is used as an example for generating strategies.

2.1. Decision-making under uncertainty of climate change

Despite the better understanding, the large amounts of new and more comprehensive data for more advanced analyses, the future impacts of climate change still come in uncertainty ranges. Furthermore, the drivers of climate change itself are also subject to uncertainty. An important factor of the climate change drivers is for example to what extent governments will live up to the agreements made to reduce the amount of greenhouse gas (GHG) emissions. Long-term decisions that are influenced by social, economical and/or environmental changes create challenges for decision-makers as they come with uncertainties (Stanton & Roelich, 2021). Deciding on investing in climate adaptation measures are subject to all above three mentioned changes and place policymakers in a challenging position. Uncertainty can be characterized as having little information of upcoming, past, or ongoing events (Walker, Lempert, & Kwakkel, 2012). Therefore, uncertainty in decision-making refers to the discrepancy between knowledge that is accessible now and the knowledge that is necessary for decision-makers in order to make the optimal strategic decision. Walker et al. (2003) specified different levels of uncertainty, ranging between determinism and total ignorance, with four intermediate levels in between, shown in Figure 2.1. In order to decide on which decision-method to apply, it is important to investigate what level of uncertainty the problem is subject to.



	Complete determinism	Level 1	Level 2	Level 3	Level 4 (deep uncertainty)		Total ignorance
					Level 4a	Level 4b	
Context (X)		A clear enough future	Alternate futures (with probabilities)	A few plausible futures	Many plausible futures	Unknown future	
System model (R)		A single (deterministic) system model	A single (stochastic) system model	A few alternative system models	Many alternative system models	Unknown system model; know we don't know	
System outcomes (O)		A point estimate for each outcome	A confidence interval for each outcome	A limited range of outcomes	A wide range of outcomes	Unknown outcomes; know we don't know	
Weights (W)		A single set of weights	Several sets of weights, with a probability attached to each set	A limited range weights	A wide range of weights	Unknown weights; know we don't know	

Figure 2.1: Overview of different levels of uncertainty (Walker et al., 2003)

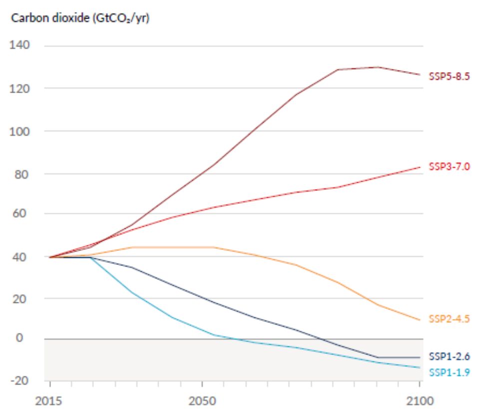
The impact of climate change is often categorized as a source of ’Level 4’ uncertainty, with the research of Helmrich and Chester (2022) and Shepherd et al. (2018) as a recent example. Level 4 implies that decisions related to long term climate adaptation projects are subject to ’deep uncertainty’ (see Figure 2.1). In case of ’deep uncertainty’ experts can not agree upon ”(i) the external context of the system, (ii) how the system works and its boundaries, and/or (iii) the outcomes of interest from the system and/or their relative importance” (Lempert, 2003). However, ’the consequences of climate change’ cover a very wide and complex spectrum. For this reason, the level of uncertainty can change for more specific problems focussed on only specific climate change consequences.

2.2. Decision-making for flood risk reduction strategies

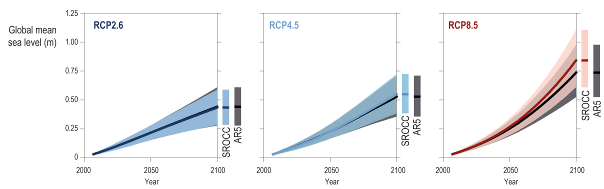
Traditionally, ’flood risk’ is defined as the exceedance probability of events of a certain magnitude and given loss. As a result, flood risk is determined by two aspects: hazard and vulnerability (S. Jonkman & Vrijling, 2008). Flood hazard can be described as the probability of occurrence of damaging water levels. Vulnerability relates to the potential damages in case of a hazard. The vulnerability to floods depends on how exposed people and assets are to flooding, and by how prone they are to suffer from damage during a flood event. Besides the flood characteristics (e.g., inundation level and speed), other factors like population growth and economic development play an important role. B. Jonkman (2022) recently mentioned the growing influence of population growth and economic development to flood risk, ’some cities doubled in population size and multiplied their gross domestic product (GDP), which resulted in a major increase in their flood risk’. These aspects and their future developments are also subject to uncertainties. Next to these uncertain variables concerning environmental conditions, societal perspectives, and preferences may also alter over time. Therefore, it can be concluded that long-term flood-risk planning are subject to different sources of uncertainty. However, in case of flood risk reduction strategies in which sea level rise is considered as the most important threat, one can argue whether these decision still fall in the deep uncertainty category.

2.2.1. The IPCC scenarios

To deal with the uncertainties related to climate change, the IPCC explores possible futures. The different scenarios present potential shifts in the climate throughout the 21st century as a function of GHG emissions. The use of scenarios makes it possible to investigate different potential evolutions of human societies and the corresponding effects on the climate. The purpose of these scenarios is to present the uncertainty linked to future human behaviour and not necessarily to predict the future, as no probabilities are linked to the different scenarios. The scenarios cover a large range of plausible futures for GHG emissions. Starting off with a scenario in which CO_2 emissions rapidly decrease to carbon neutrality by 2050 and become negative before the end of the 21st century, to a scenario in which the CO_2 emissions continue to climb sharply to double present emissions levels in 2050 (Pörtner et al., 2022). The different emission scenarios are projected in Figure 2.2a. Based on the emission scenarios, different sea level scenarios are identified.



(a) Future CO_2 emissions in the five illustrative scenarios



(b) Time series of Global Mean Sea Level emission scenarios RCP2.6, RCP4.5 and RCP8.5

Figure 2.2: IPCC projections presented in different scenarios (Pörtner et al., 2022)]

Although there is no probability linked to the different scenario's and the sea level projection still come with uncertainty ranges, according to the theory flood risk reduction strategies fall in the 'Level 3' uncertainty category (Figure 1.3). In Appendix A.1, a more elaborate discussion of the different scenarios can be found.

2.2.2. Methods to deal with uncertainty

Over the past decades, research has looked into methods on how to make decisions under uncertainty. The approach for dealing with Level 3 uncertainties relies on the assumption that the small number of future worlds can be sufficiently described to establish resilient policies that will result in the positive outcomes in the majority of them (Marchau, Walker, Bloemen, & Popper, 2019). Scenarios are used to describe these future worlds. The best strategy is considered to be the strategy that results in the most desirable outcome across the range of possible scenarios, and on the other hand minimize the most regrettable outcomes. The downside of this approach is that in case the range of future worlds turns out to be incorrect, the adverse possible consequences could be severe (Marchau et al., 2019). Furthermore, if scenarios differ a lot from each other, it can be questioned how cost optimal the decision will be. Long term decision-making for flood risk reduction strategies faces this challenge. If the Level 3 approach is used to decide on the flood risk reduction strategy, the result will most like involve expensive measures (especially in case of a broad range of scenarios). The downside of this approach is that there is a chance of implementing too many measures, which results in unnecessary societal disruption and spending amounts of money.

In order to prevent these undesirable outcomes, different approaches are applied. Irrespective of climate change being subject to deep uncertainty or not, methods created to deal with deep uncertainties pose an alternative to prevent the negatives outcomes like over-investing. Recent research has shown that, to adequately incorporate the uncertainties of climate change, decision methods should be grounded on 'robust' and 'adaptive' ideas (Y.-O. Kim & Chung, 2017). A 'robust' strategy is defined to have the ability to perform well over a range of future scenarios (approach for level 3 uncertainties). Secondly, an 'adaptive' method adjusts its strategy based on the lessons learned from past events and the output from continuous monitoring. It is assumed that when a long-term strategy is robust and adaptive, a decision-maker can be confident that the created strategy made now, will continue to apply, and measures will be available to deal with changing conditions. So-called DMDU methods are able to make decisions that are robust and adaptive. Different DMDU methods have been used in research over the past decade to deal with the uncertainty related to climate change, among them was the DAPP method. In the past 10 years, the method has been put into practice in multiple cases; a climate-resilient pathways for the Thames Estuary (Ranger, Reeder, & Lowe, 2013), flood risk management in New York (Rosenzweig & Solecki, 2014), the Rhine and Meuse Delta in the Netherlands (Programma, 2015) and a fluvial, pluvial and coastal flooding plan for Shanghai (Ke, Haasnoot, & Hoogvliet, 2016).

2.3. Adaptive Pathways

The concept of adaptive planning, specifically the introduced DAPP approach, addresses the challenges of robust and adaptive long-term planning. Adaptive pathway planning investigates alternate orderings of investment decisions to realize objectives over time in the presence of uncertain future developments (Wise et al., 2014), (Ranger et al., 2013). The core of this method is proactive and dynamic planning, allowing flexibility and adaptation in response to the unfolding future. The methodology is based on the idea that investment choices (or actions) have a finite lifespan and may no longer meet goals if circumstances change, i.e., when a threshold is crossed, known as the Adaptive Threshold Point (ATP) (Kwadijk et al., 2010). In a flood risk reduction strategy, for example, the rate of sea level rise can result in a minimum safety level no longer being met. When an action no longer fulfils the objective, new actions are required to meet the standards again, leading to a variety of alternate pathways.

These pathways can be visualized in a pathway map, similar to a decision tree or metro map, illustrating different routes to reach an "end destination" (Haasnoot et al., 2013). Such a metro-map was already briefly discussed in Section 1.1 and shown in Figure 1.2. The trade-offs between their costs and benefits will determine which pathways are preferred over others. It is crucial to understand the terminology correctly for the proper application of adaptation pathways and, therefore, this research.

A pathway map showcases all available pathways, and the specific route followed depends on how the future unfolds. If there is only one initial decision moment, the strategy is considered static. However, if there are opportunities to make decisions based on available knowledge at different points in the design process, the strategy is flexible or adaptive. The number of different starting measures (first action) defines the number of strategies. For the sake of clarity and assurance of correct understanding, the key terminology used in this chapter and the rest of this research is presented in the grey text box below.

While adaptive planning offers advantages, it also presents challenges and weaknesses compared to static approaches. Some challenges include uncertainty in future developments, potential trade-offs between short-term and long-term objectives, and the need for continuous monitoring and adjustment. In contrast, static approaches provide a more straightforward and predictable framework but may lack the ability to respond effectively to changing circumstances.

Overview Key-terminology

- **Decision Moment:** A decision moment in a project refers to a moment during which a decision-makers has the opportunity to make a choice on how to proceed with the project plan.
- **Pathway Map:** A pathway-map shows all the possible **strategies** that can be followed. The number of different strategies is determined by the number of 1st measures.
- **Adaptive Strategy:** A pathway through the metro map that consist of more than 1 action. There is a moment, one can **adapt** how the future unfolds. The future will tell which of the pre-formulated pathways has been followed.
- **Static Strategy** In this thesis, a strategy is considered to be static in case there is no intended decision moment during the entire project horizon.

3

Capture the Value of Flexibility

As described in Section 1.1, multiple approaches exits to develop or evaluate flood risk reduction strategies. Certain methods focus on the uncertainty, other focus more on incorporating flexibility. This chapter is divided into two sections. Section 3.1, evaluates different existing methods. From this analysis, the most important features of these methods were noted and used to develop a new framework. Next, in Section 3.2, all the variables that are included in a flood risk reduction strategy were discussed. For every variable it was investigated, whether it is reasonable (based on literature) to assume that the uncertainty of the variable would reduce when time passes.

3.1. Analysis of Evaluation Methods

Various techniques and methods have been created to support in decision-making when there is a high degree of uncertainty. These approaches emphasize the importance of taking measures to decrease the susceptibility of strategies to unpredictable future events. Below, different approaches are discussed and examples of its applications are provided.

3.1.1. Robust Decision Making

The objective of RDM, is to develop decision strategies that are robust and likely to perform well under a wide range of possible futures.(Lempert et al., 2006). The complexity of many projects involves multiple stakeholders, conflicting objectives, and limited information, making it challenging to anticipate all potential outcomes. By evaluating various options and potential outcomes, including worst-case scenarios, decision-makers can identify strategies that are robust and can perform well across multiple possible futures. Robustness is a critical aspect of RDM and refers to the ability of a decision strategy to perform well even under conditions of high uncertainty or ambiguity. Identifying strategies that are robust helps decision-makers minimize the risk of negative outcomes and increase the resilience of their systems. Often, a robust strategy is a referred to as a 'no regret' strategy. In the research of Vavatsikos et al. (2022), a study was conducted for a wind energy project. The article introduces a framework that combines two methods, namely the fuzzy extension of TOPSIS and Monte-Carlo (MC) analysis. In simple terms, these methods use human language to evaluate criterion weights and rate alternatives provided by decision makers. Then, a MC-analysis generates a large number of random samples based on distributions provided by the decision-maker. By doing this, it is possible to estimate how robust the chosen solution is, in a more accurate manner. This approach aims to improve decision-making processes in complex scenarios.

Additionally, RDM aims to increase transparency by taking into account various objectives and criteria in the decision-making process. As a result, decision-makers can have a better understanding of the advantages and disadvantages of different options and outcomes. This enables more informed decisions making that balances competing priorities. One example of trade-offs in decision-making can be found in a study by Lempert et al. (2006) that used RDM to analyse water management strategies in the Los Angeles region. The study identified trade-offs between different water management strategies, such as increasing supply reliability versus reducing costs, and increasing water quality versus reducing environmental impacts.

Another study by Groves, Molina-Perez, Bloom, and Fischbach (2019) looked in water resource planning for the Colorado River Basin. Here the trade-off between the risk of low stream flows, pool elevations and costs were evaluated. The research stressed the ability of RDM to facilitate so called 'deliberation with analysis' (Groves et al., 2019). This term describes the process of decision-making where people or groups carefully and methodically consider options and potential outcomes before reaching a final conclusion. It involves careful consideration of relevant information, weighing of alternative options, and evaluation of the potential consequences of each decision. This approach is often used in complex situations where there are multiple factors to be considered and where the stakes are high.

The method is also applied for studies outside the field of water management and flood risk. Molina-Perez (2016) used RDM to develop the best policy on behalf of the Green Climate Fund (GCF). Here the metrics of performance for the benefits were temperature rise and stabilization of GHG emissions. As 'costs' the economic costs of policy intervention but also the difference in consumer welfare between a specific policy and the best policy for a given future were included. By explicitly considering trade-offs, decision-makers were able to identify robust strategies that performed well under a range of possible futures while balancing competing priorities.

The primary goal of RDM is to create strategies that are both cost-effective and resilient; and perform well under a wide range of possible scenarios. By using this approach, decision-makers can minimize the risk of negative outcomes. By including multiple criteria, a transparent performance overview is achieved.

3.1.2. Real Option Analysis

Adaption pathways have experienced an increase of consideration in economic evaluation studies. An example is the implementation of ROA, discussed in the research of Buurman and Babovic (2016) and Woodward, Kapelan, and Gouldby (2014). One of the fundamental premises of ROA is that it is able to capture and value flexibility. The theory of real options finds its origin in the financial option theory, including the Black-Scholes formula (Myers, 1977) and the simple binomial discrete time option pricing formula (Cox, Ross, & Rubinstein, 1979). A financial option is defined by the right, but not the requirement, to buy or sell a financial asset by for a specified price. "Real Options' exist when the underlying option corresponds to a real asset like important information, a business opportunity or buying land. In the context of flood risk reduction strategies, a real option can refer, for example, to the option to invest in a protection measure. So, in contrast with the traditional planning approach in which only one-off investment options are recognized, the real options' concept is able to take management flexibility and volatility into account by enabling changes to an investment in case new information become available in the future (Buurman & Babovic, 2016).

In a traditional CBA, uncertainty is included by expected values depending on respective probability distributions. The downside of this approach is that it connects a 'now or never' quality to the decision moment. This quality is only suitable in case there is no flexibility. However, when the possibility exists to modify the decision, a traditional CBA tend to undervalue it. The ability to choose a different course of action or to decide to postpone an action until more information is available, results in the opportunity to limit the negative effects of making a poor choice while also maximizing the positive effects of the newly available information. This aspect is the main premise of the adaptive planning concept. Figure 3.1 shows how ROA fits with other quantitative evaluation methods.

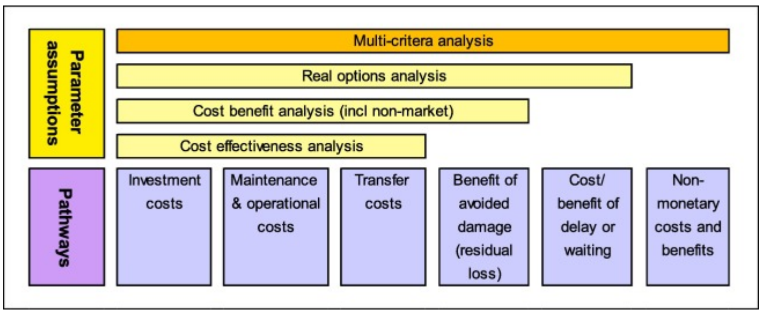


Figure 3.1: Different evaluation methods as corresponding qualities (Stroombergen & Lawrence, 2022)

Traditionally, two types of real options can be distinguished; real options 'on' a system and real options 'in' a system (Geltner & De Neufville, 2012). Real options 'on' a system are linked to external factors of a system and lies closer to financial options. An example of a real option 'on' a system is the option to defer or abandon a project. On the other hand, real options 'in' a system are options that are incorporated into the design of the system, for example making allowance for future expansion of a levee by over-designing the foundations. Both options 'in' as options 'on' a system are valuable for climate adaptation plans. In addition to financial option analysis, ROA is being applied to diverse fields like the management of water supply (Steinschneider & Brown, 2012), renewable energy (L. Liu, Zhang, & Zhao, 2019), and infrastructure systems (Palin et al., 2021). In the past decade, the theory of real options has been utilized in flood risk management to construct cost-effective adaptation measures in order to deal with the uncertainties of climate change.

Research showed many different possibilities to formulate decisions as real options in climate adaptation strategies. Woodward et al. (2014) formulated the decision to raise a levee or not as a real option, and Steinschneider and Brown (2012) formulated the option to transfer water between the water supply agency and nearby flood control reservoir as a real option. Table 3.1 shows an overview of different applications of real options applied in different research in to climate adaptation strategies. The first thing that can be pointed out is that all research is relatively recent, as it all dates back no more than 10 years. This confirms the growing interest in evaluation methods that include flexibility. Another finding from this review is that multiple modelling methods were used and that not a single method stands out.

3.1.3. Extended CBA

The study of de Ruig (2020) and Haasnoot, van Aalst, et al. (2020) extended the traditional CBA framework to evaluate adaptation pathways. They both extended the time horizon of the traditional CBA and also included evaluation of sequential measures. The method of de Ruig (2020) approach incorporates both the temporal and spatial dimensions of climate change impacts and evaluates a range of adaptation measures and their timing to identify the most cost-effective and efficient pathway. Similarly, (Haasnoot, van Aalst, et al., 2020) extended the traditional CBA framework by incorporating multiple scenarios and an extended time horizon to evaluate sequences of investments or adaptation options. The most effective pathway is determined by the climate and socio-economic scenario (SSP-RCP). Transfer costs are included that quantify the path-dependency of options.Both methods build on the traditional CBA framework and provide a more thorough analysis by taking into account a range of factors and considering the long-term effects of climate change. In Figure 3.2 a schematization of the framework is depicted.

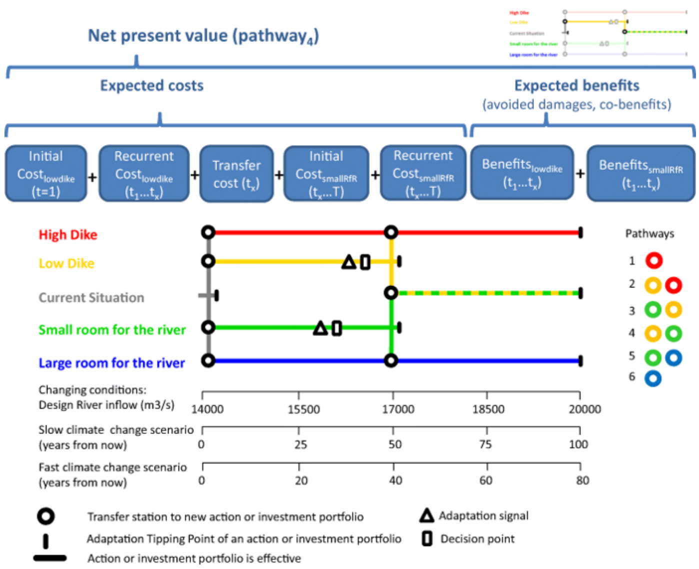


Figure 3.2: Depiction of Economic Evaluation Framework that assesses Adaptation Pathways (EEFAP) showing different pathways (sequences of measures). In the upper part, the proposed method is described. On the x-axis different climate scenarios are shown, which determines the ATP,and ultimately determine the optimal strategy.

Table 3.1: Different ways how to include real options in climate change adaptation strategies found in literature. For every research, the context and the modelling method is provided.

Real Options in Climate Change Adaptation	Context	Modelling method	Source
Possibility to increase levee height or not, limited to certain decision moments	Investments in coastal defences	Monte Carlo Model	(Linquiti & Vonortas, 2012)
Option to invest in extra measures (bio-retention and permeable pavement)	Urban surface water flood risk management	Trinominal tree model	(H. Liu, Wang, Zhang, Chen, & Fu, 2018)
Continuous option to invest in coastal defence	Finding the optimum timing for investment of coastal flood adaptation	Dynamic Programming Model	(M.-J. Kim, Nicholls, Preston, & de Almeida, 2019)
Decision variables: raising the crest level of defences, increasing the capacity of the defences for future expansion, and the level of maintenance applied	Flood risk management for the Thames Estuary	Multiobjective genetic algorithm	(Woodward et al., 2014)
Option to implement, delay or abandon a set or individual measures	Flood mitigation plan for riverine area	Binominal Tree	(Ryu, Kim, Seo, & Seo, 2018)
Option to transfer water between the water supply agency and nearby flood control reservoir	Reservoir management adaption to uncertain climate	- not clear	(Steinschneider & Brown, 2012)
Invest in widening a flood defence beforehand in order to create the real option for an increase in height if needed	Flood risk management for the Thames Estuary		(H. Liu et al., 2018)
Three investment decisions which can be implemented on 5 different time steps	Water resource planning	Optimization model	(Erfani, Pachos, & Harou, 2020)

3.2. Reduced Uncertainty

As discussed in Section 2.2, a flood risk reduction strategy is subject to various uncertainties. The performance of the strategy could therefore be increased in case there is a possibility to base decisions on new information. The 'updated' knowledge which could lead to reduced uncertainty is one of the possible drivers of the added value of adaptive pathway planning. Figure 3.3 illustrates this principle of 'updated data' and is also referred to as the value of time. The schematization depicts two pathway maps. Map 1 illustrates the scenario no updated knowledge is used, and Map 2 shows a scenario in which future decision moments have access to new knowledge. However, although time passes, not all input variables will experience a reduced uncertainty. In this section, all the variables are evaluated in order to find whether evidence is found to assume a reduction in uncertainty. Earlier in this research, SLR and socio-economic growth were mentioned as important drivers of the increased flood risk. Section 3.2.1 and Section 3.2.3 focus on these two variables, and the other remaining variables are discussed in Section 3.2.5.

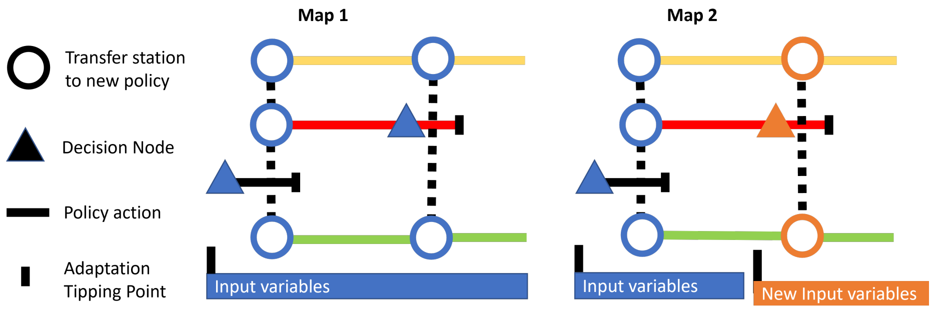


Figure 3.3: Altered Adaptation Pathway map to illustrate the asset of new knowledge. Map 1 illustrates an adaptive plan in which the data available at the start is used during the whole time horizon. In Map 2, new input variables, based on knowledge retrieved over the past time-span, are included at the decision node and transfer station, marked in orange.

3.2.1. Modern Sea-Level Rise Projections

For this research, a study was conducted to find a trend in the uncertainty ranges of the past SLR projections. A possible trend could then be used to predict the future projections. Past SLR and the future predictions drive the urge for investments in coastal flood risk projects. When the sea level increases, so will the risk of flooding. The global mean sea level (GMSL) has risen about 25cm in the last 180 years (IPCC, 2007). However, the fact that the rate has been increasing over time is alarming. Consequently, there is a high demand for SLR projections at both global and local scale. In the past 200 years, the observations of the sea level have mainly been based on tide gauge measurements. This data, starting around 1700, provides insights into the historic sea level trend. Technological advancements like satellite altimetry (1992) and high precision gravity measurements (2002) have enhanced our knowledge of global SLR and our understanding of the magnitude and relative contributions of the different processes causing sea level change tremendously (Ablain et al., 2015).

Since 1980, there was a growing awareness of the potential instability of the West Antarctic Ice Sheet and the probable effect of global warming (Garner et al., 2018). These concerns led to the first modern projections of the 21st century GMSL. The models initially focussed on basic statistical models of the relation between global-mean temperature and sea level. Quickly, these models got more extensive as it shifted to methods that integrated model-and literature based projects for specific processes (e.g (Hoffman et al., 1983)). This was done with the goal to assess the likelihood of future SLR. The importance of these projections were recognized by policy-makers, which led to the establishment of different independent councils, one of which was the IPCC in 1988. Over the past years, many projections have been published in which different techniques are applied, all with their own results and uncertainty ranges.

Many factors influence the uncertainty of the projections, one of which is the contribution of the drivers of SLR. Among others, Frederikse et al. (2020) identified three main drivers that contribute to GMSL change on timescales ranging from decades till millennia. First, the net loss of mass from glaciers and ice sheets to the oceans; secondly thermal expansion and thirdly changes in non-glacial water storage on land, including groundwater aquifers and water held in rivers or behind dams.

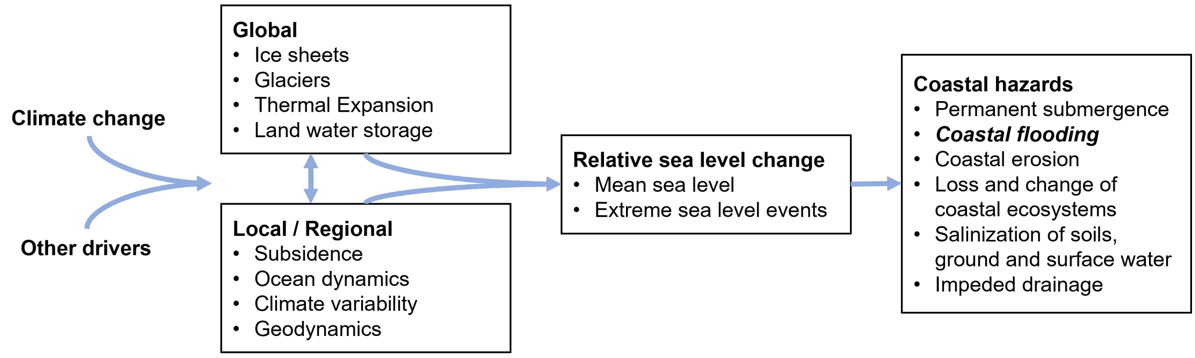


Figure 3.4: Schematic illustration of the drivers of sea level change, (Pörtner et al., 2022)-adjusted

The Antarctic and Greenland ice sheets are often considered individually because in case they were to melt completely, it would result in a SLR of 57m and 7m respectively. All the other glaciers combined would 'only' raise the sea level by 0.32m (Farinotti et al., 2019). Next to these main drivers, other drivers that contribute to relative seal level change are presented in Figure 3.4. As shown in the figure, a distinction is made between global and local/regional drivers. In recent literature (e.g., (Edwards et al., 2021)), the largest contributor to the uncertainty of future SLR is considered to be the magnitude, amount and timing of the Antarctic ice sheet contribution.

Despite the scientific advancements, the upper bound of the sea level estimates remains highly speculative. There is no universally accepted best-estimation technique or a single agreed upon probability distribution (Kopp et al., 2017). Slangen, Haasnoot, and Winter (2022) assigned the differences in the projections to (a) the choice of modelling method (e.g., process-based, semi empirical), (b), the choice of climate scenario used to drive the models, or (c) the choice of data source for the contributors. To refrain from choosing a particular projection, decision makers often use the IPCC projections, which are an ensemble mean or consensus estimate.

In Appendix A.2 a more elaborate discussion, substantiated with figures, about the studies into past projections can be found. The conclusion from this study is that no scientific grounds could be found that justified the reduction of the uncertainty range of future sea level projections. Initially, the better understanding and more scientific advancements led to a reduction of the uncertainty ranges. However, since 2007 this trend reversed and greater ranges were projected. According to DeConto and Pollard (2016), this increase reflects the uncertainty about the maximum contribution of the Greenland and Antarctic Ice Sheets. It is sensible to say that the increase of understanding has also resulted in an increased of understanding of the elements that are not understood yet. The latest IPCC report showed a similar uncertainty band, except the 95th quantile outliers being greater. Finally, based on the IPCC Synthesis Report, the United Nations panel emphasizes the critical nature of the next decade, stating that "The Next Decade Is Crucial" (Plumer, 2023). This implies that the forthcoming decade could provide significant insights into future projections and their implications.

3.2.2. Damages

As described in Section 2.2, flood risk is determined by hazard and vulnerability. Evaluating potential economic damages from flooding events covers a broad spectrum, influenced by the size of the flood event. Economic damages can be classified into two main categories: direct and indirect damages. Direct damages are physical losses that occur as a direct result of a flooding event, such as damage to buildings, infrastructure, and personal property. Indirect damages are economic losses that result from the disruption of economic activity caused by the flooding event. The damages can further be classified as tangible and intangible damages. Tangible damages refer to physical losses that can be easily quantified, such as damage to buildings, vehicles, and personal property. On the other hand, intangible damages are losses that are more difficult to quantify, such as loss of life, health, and quality of life. Table 3.2, shows a classification of various types of damages by S. N. Jonkman et al. (2008).

In this research, only direct physical damages are included in the risk assessment. This procedure consists of three elements which are: 1) determination of flood characteristics, 2) assembling data on land use and maximum damage amounts and 3) application of stage-damage functions (S. N. Jonkman et al., 2008).

Table 3.2: Overview of different dimensions of flood damages[(S. N. Jonkman et al., 2008)]

<table>
<tr><th colspan="2">Category</th><th>Tangible & Priced</th><th>Intangible and unpriced</th></tr>
<tr><td rowspan="2">Direct Damages</td><td>Physical damage</td><td>Loss of capital: residences, vegetation, cars, industry, infrastructure)</td><td>- Casulties,
- ecosystem pollution,
- Historical and cultural losses</td></tr>
<tr><td rowspan="2">Interruption of business</td><td>Interruption of production (within flooded area)</td><td>- Societal disruption
- emotional damages</td></tr>
<tr><td>Indirect damages</td><td>Interruption of production (outside flooded area)</td><td>- psychological traumas,
- Undermined trust in public authorities.</td></tr>
</table>

These three elements were evaluated in order to determine whether they are subject to reduced uncertainty when time passes. The first element involves determination of flood characteristics, which are prone to model uncertainties and will therefore not benefit from more time. For the second element, the uncertainty in captured in the future developments of the land(use). The land-use of the project-area can change overtime due to for example development projects. Besides, in case of land-use change or not, the value of the land can also change overtime. Multiple factors play a role in this like demand, rules/regulations or environmental influences. The development of the maximum value is often only captured in the economic-growth factor, which will be discussed separately below. For the other factors, the uncertainty can not be quantified, especially not in general terms. The third element concerns the damage curves. According to Wever (2022), damage models inherently include uncertainty. Nevertheless, for certain categories such as agriculture, this uncertainty can be reduced through calibration. Conversely, for land-use categories like residential and critical assets, reducing uncertainty is more challenging, and damage can vary substantially even within a local area. Furthermore, this research showed that the accuracy level of the damage estimate depends on spatial data such as elevation maps, as inundation depth, a factor in damage estimation, is affected by the precision of the elevation map. For the final element, the uncertainties are mostly model uncertainties.

3.2.3. Socio- Economic growth

The economic growth rate is country and even site specific and it the context of flood risk, it describes how the value of the project area will evolve in the future. In case of a strong economic growth of the area, more (expensive) measures can become economically desirable. Many factors play a role in this rate such as the economic growth indicator like the Gross Domestic Product but also the developments plans for the area. Barro and Lee (1994) looked in to drivers of (socio) economic growth and identified many drivers from which 6 are considered as most important. These are natural resources, physical capital or infrastructure, population, human capital, technology and law. Each driver contains its own uncertainty, one more than the other. Natural resources or the population, for example, are not likely to change drastically (Barro & Lee, 1994). The research also showed that the growth also depends on the initial GDP per capita. When relatively low, it is more likely to grow quicker. When looking for example at a time horizon of 100 years, the uncertainty range highly depends on the current level of development. When there is a lot of area available for development, the uncertainty range will be greater than in the case of a fully developed project area. The conclusion that can be drawn is that, whether the uncertainty range will change overtime, is highly dependent on the specific project area.

3.2.4. Costs of coastal defences

Understanding the costs of building or upgrading coastal defences is an important consideration in the response to increased flood risk. S. N. Jonkman et al. (2013) reviewed the unit costs and identified 5 factors that play an important role.

One of the key factors that influences these costs is planning and engineering. This includes a variety of expenses, such as feasibility studies, site investigations, and modeling.

Another major cost component is material costs. This encompasses all the materials required for the construction of the coastal defence structure, and typically accounts for a significant portion of the overall unit costs. Optimizing material usage and selection can result in substantial cost savings, but the prices of materials can vary depending on a range of factors, including their quality, availability in the local area, and the distance they must be transported to the construction site.

Labour costs are another significant expense associated with coastal defence structures. These costs can vary depending on the prevailing wages in the area, as well as the experience and expertise of the construction workers. Implementation costs are also a critical consideration when planning and constructing coastal defence structures. Two main factors that influence implementation costs are land use and the type of area where the construction will take place. The area required for construction typically increases linearly with the height of the structure, and obtaining the necessary land can be both costly and time-consuming. In urban areas, space is often at a premium, and large construction projects may require the removal of existing buildings. This can be a controversial and expensive process that must be carefully managed to ensure that the costs are justified by the benefits.

Finally, it is important to consider the ongoing management and maintenance costs associated with coastal defence structures. These costs represent an ongoing annual stream of expenses that are required to ensure that the structure remains effective over time.

The uncertainty of the above-mentioned costs are partly contained in both the economic growth as the inflation rate. However, other developments like technological advancement or stronger building regulation can influence the costs as well. As these are very uncertain, it is concluded for now that no consensus can be found about the value of time for the costs of measures. The uncertainty of the economic growth was discussed earlier, and the inflation rate is discussed in the next section.

3.2.5. Other variables

Besides the uncertainty of SLR projections, socio-economic growth and the costs of measures, other stochastic variables contribute to the uncertainty of flood risk reduction strategies. Below, the variables are discussed individually if it is reasonable to assume that the uncertainty will change over time.

- **Extreme Water Levels**
  With the use of hydrodynamical or statistical models, the frequency and intensity of extreme sea level (ESL) events can be estimated. By applying an extreme value analysis of the site specific water level data, water levels for various return periods are obtained. The accuracy of this analysis relies on the extent of the time period of the available data and on the accuracy of the measurements. An ESL event is composed of the mean sea level, the storm surge and tide. As discussed above, the first mentioned driver is projected to increase in the coming years. Consequently, SLR will lift the platform of tides and storm surges. Even a minor increase in sea level can have substantial impact on the frequency and intensity of flooding because of the log-linear relationship between the occurrence of floods and its height. So a consequence of SLR, events that are currently rare (e.g., a 1 in 100 year event) can occur on an annual basis in the future. Of course, this depends on the SLR-scenario, but also on the local water-level variability. Locations with minimal water level variability due to tides and storm surges, (i.e., short tailed flood level distributions), are more prone to be affected (Almar et al., 2021). At some locations, particularly located in low-latitude regions, even the low emission scenario (RCP2.5) can result in annual occurrence of historically rare events by 2050 (Oppenheimer et al., 2019). In Figure A.4 in the appendix, the varying impact of SLR at different locations is depicted. Next, assuming that the extreme value analysis is based on a time period not longer than 50 years, it is reasonable to assume that an extra 40 years of data will have impact on the results. However, the uncertainty in the future extreme water-levels is mainly driven by the SLR development. Since the SLR projections are treated earlier, no additional conclusions about the reduced uncertainty in ESL are drawn.

- **Inflation**
  Due to inflation, investments cost and O&M costs can increase. When general prices go up, each unit of currency will buy fewer goods or services, so inflation means a decrease in the purchasing power of money. Most economist prefer a stable and low inflation-rate (Hummel, 2007). Monetary institution have the power and the responsibility to manage the monetary policy and sustain a proper inflation rate. Rare external forces (e.g., war or epidemics) can have a great influence on the inflation rate. However, one can argue that these events are very difficult to predict and are therefore not included in the uncertainty ranges of the inflation rate. For the inflation-rate, no reason was found that the uncertainty ranges will change over time.

- **Discount rate**
  Future costs and benefits are discounted back by using the so called 'discount' factor to present day values. The discount factor for large infrastructural projects is often a political and country specific decision. Consideration to the rate must be given, as the rate can have a significant impact on what turns out to be the most cost optimal strategy (Woodward et al., 2011). Since the discount rate is a deterministic value in this research, this input variable will not be updated for a later decision moment and will therefore not experience a reduced uncertainty.

3.2.6. Level of Adaptability

Above, it was discussed which variables would experience reduced uncertainty at future decision moments. However, the next question that arises is how flexibility, or options to adapt, can be created in a strategy. Two important factors are the SLR rate and the timescale of an adaptation measure. The timescale of an adaptation measure concerns two aspects; (i) the envisioned functional lifetime of the measure and (ii) the available and required timescale (Haasnoot, Kwadijk, et al., 2020). When for example adaptation measures with a lifetime of +100 years are considered for a SSP5-8.5 SLR-scenario, it might lead to a situation in which decisions should be made quickly and minimal information about the actual SLR is available yet. In this situation, it is difficult to take no- or low-regret decisions, which is considered as one of the premises of adaptive pathway planning. Therefore, when options with shorter envisioned timescale and shorter lead time are considered, the strategy becomes more flexible and the value of adaptive pathways is used more.

As discussed before, the framework should be able to evaluate strategies that vary if flexibility. The difference is created by alternating between measures with different envisioned functional lifetimes and required timescales. The envisioned functional lifetime is determined by the protection level of the measure, which then depends on two aspects. For example, when it has been decided that a levee should function for 50 years, the actual height also depends on for which SLR-scenario the levee is constructed. The second mentioned challenging aspect concerns the timescale which refers to the amount needed for the measure to be completed (design till construction). This amount of time is also referred to as lead time. The moment a decision needs to be made it defined by the moment of the ATP, minus the lead time. Haasnoot, Kwadijk, et al. (2020) defined SLR categories to illustrate how this selection will affect the timing of the ATP. The category is based on the amount of SLR a measure is build for. When a measure is build for a 0.5 SLR, it is not a matter of if, but when this moment arrives, there is little uncertainty that this level is crossed within the near future. It doesn't really matter which projections are used. However, for more extreme measures build for a 1.5m SLR, the bandwidth of timing becomes larger. There is a high uncertainty if this threshold is even met. The timing of the ATP is no longer irrespective of the sea level scenario that is used, like the situation of 0.5m SLR. Figure 3.5 shows how a slr-category impacts the bandwidth of the ATP timing. This refers to the earlier described envisioned lifetime, as impacts the time range in which the ATP can be expected.

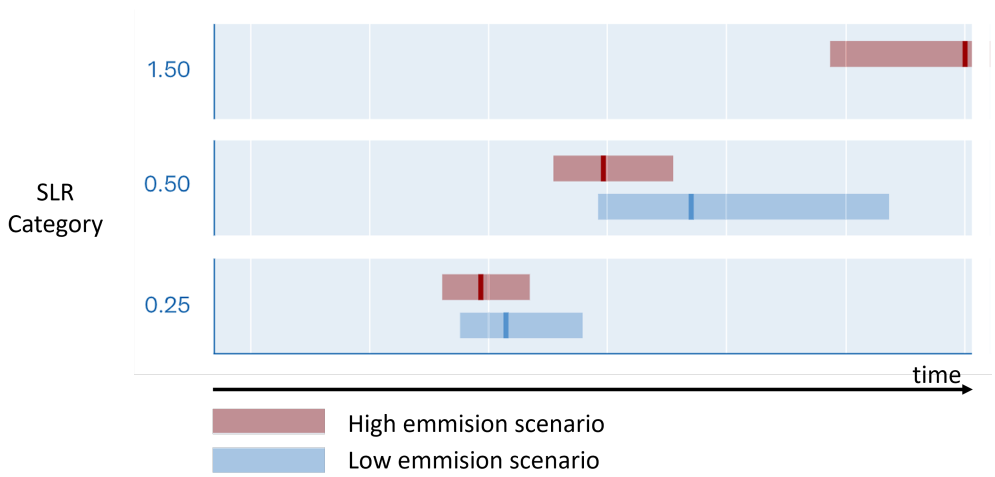


Figure 3.5: Consequence of SLR category and scenario(Haasnoot, Kwadijk, et al., 2020) - adjusted

4
Framework

In this chapter, the developed framework that was employed in this research is explicated. The findings from the previous chapter that answered sub research questions 1 and 2 were used in the development. One of the findings concluded that the factor of SLR uncertainty will benefit from reduced uncertainty when time passes. Therefore, this framework is constructed in such a way that at a so called 'decision' moment, the decision-maker has access to more knowledge concerning this variable. A visual representation of the sequence of steps undertaken is depicted in Figure 4.1, by means of a flowchart. For the purpose of clarity, the framework is segmented into four distinct sections. Each section covers a specific topic and is described below.

A. **Project Area Characteristics:** In this section, the local situation of the project area is examined. The local situation determines the current flood risk and the projections for the future.

B. **Specification of Adaptation Strategies:** In this section, the characteristics of the included adaptation strategies are described. For every strategy, the impact on the risk and the associated costs are defined.

C. **Cost-Optimal Measure** Based on the type of adaptation measure and the current flood risk, a cost optimal measure can be defined. This depends on which initial SLR-scenario is considered.

D. **Economic Evaluation:** Once the measure heights are defined, the strategies can be economically evaluated. This is done by a MC-analysis. The output of this analysis are economic performance parameters which can be used for comparing the different strategies.

4.1. Section A: Project Area Characteristics

For any project area, the current and projected future flood risk can be calculated. This provides insights in the risks and motivates to what extent measures are needed. As mentioned earlier in Section 2.2, flood risk is defined by the probability of a flooding and the potential damage in case of such flooding.

4.1.1. Probability of flooding

To derive the probability of flooding, the extreme water events, SLR and the current protection level are evaluated. These three factors are described individually below.

Extreme water Events

The concept of extreme water events is integral to determining the probability of flooding, which refers to the likelihood of a flood occurring within a given time frame. To determine the probability of flooding, historical water level data is analysed using statistical models. The Gumbel distribution is well-suited for modelling rare and extreme events and is applied in other studies like (Lendering et al., 2020), making it a reasonable choice for this analysis. The Gumbel distribution is defined by two parameters: the location parameter (μ) and the scale parameter (β). The location parameter represents the location of the distribution's peak or centre, while the scale parameter represents the width of the distribution.

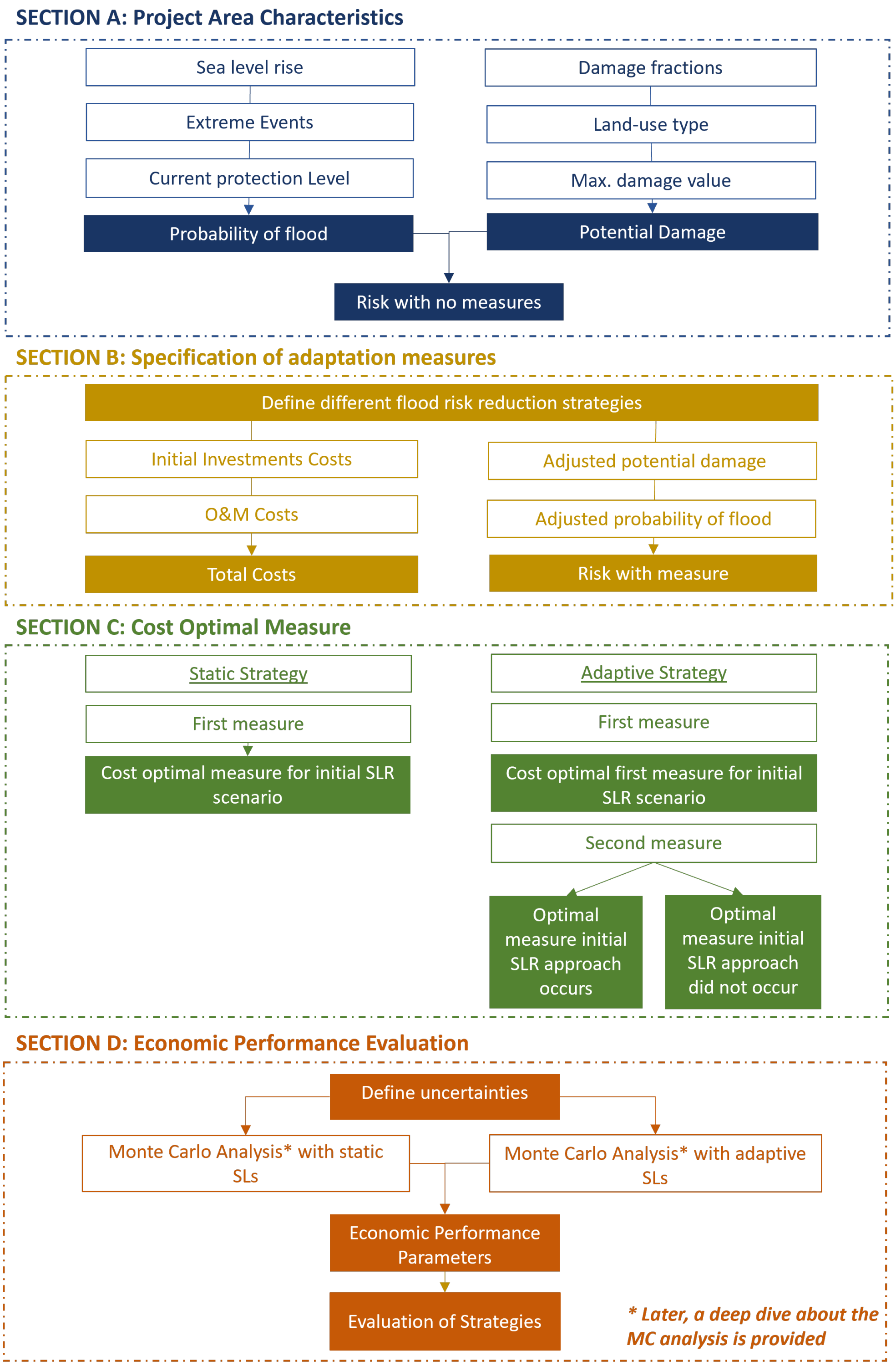


Figure 4.1: The framework is built up in 4 sections: A,B,C and D. Every section is discussed individually.

Once the parameters of the Gumbel distribution have been estimated, the probability of an extreme event of a given magnitude can be calculated using the distribution's cumulative distribution function (CDF), see Equation 4.1. The CDF gives the probability that a flood event will be less than or equal to a certain magnitude. For example, the probability of a flood event with a magnitude greater than or equal to a certain threshold can be calculated by subtracting the CDF value from 1, an example is plotted in Figure 4.2.

The inverse of the Gumbel CDF gives the flood magnitude that corresponds to a given probability level. This is also called the quantile function or the inverse distribution function. The inverse of the Gumbel CDF is given in Equation 4.2.

$$F(x;\mu,\beta) = e^{-e^{-(x-\mu)/\beta}} \tag{4.1}$$

$$x = -\ln(-\ln(F)) * \beta + \mu \text{ in which } F = 1 - 1/P \tag{4.2}$$

In which:
$F()$ [-] = CDF function; probability of water level is greater or equal to given value
μ [-] = Location parameter
β [-] = Scale parameter
x [m] = Water level
P [-] = Return Period

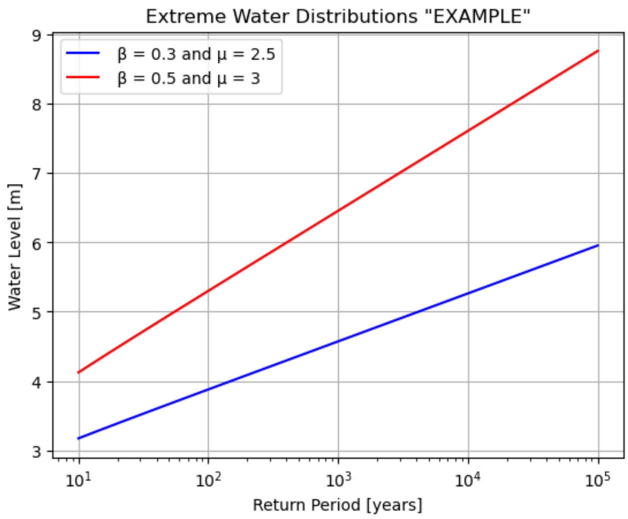


Figure 4.2: Example of Extreme water level distribution using Gumbel, with arbitrarily chosen parameters.

Sea Level Rise

The only climate factor that is included in determination of future risk in this study is SLR. SLR is important for projecting how the risk will develop over time. As the sea level rises, the risk of flooding in coastal areas increases. The potential impact of sea level risk on flood risk must be assessed and factored in the calculation of future flood risk. Equation 4.3 shows how Equation 4.1 is adjusted to include SLR. Figure 4.3 shows the impact of SLR on the return period of extreme water levels. The water levels for the same return period will be higher, as can be seen in Figure 4.3. Other climate change factors, like increased surges, are not taken in to consideration in this research.

$$F(x;\mu,\beta) = e^{-e^{-(x-\Delta SLR-\mu)/\beta}} \tag{4.3}$$

Current Protection Level

The actual protection level of a project area is a critical factor when translating extreme water levels to actual flood events. The protection level refers to the level of protection that the area currently has in place, which is determined by multiple of factors including the elevation of the land, and the presence of flood protection measures such as levees or flood walls.

For example, if a project area is located in a low-lying coastal region and there are no flood protection measures in place, it will be more vulnerable to flooding than an area with higher elevation and robust flood protection measures.

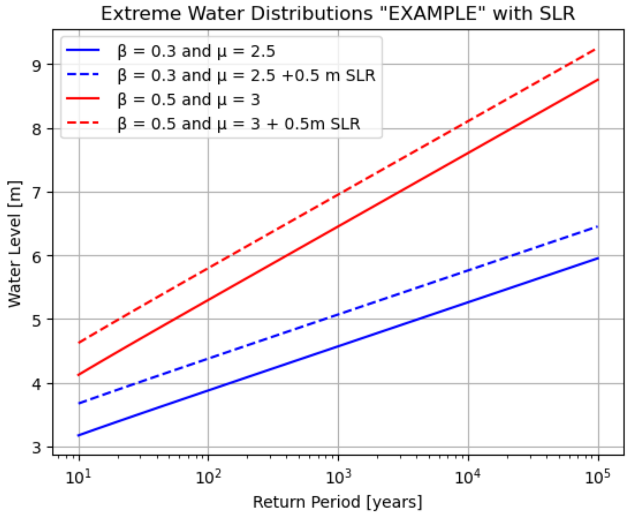


Figure 4.3: Example of Extreme water level distribution using Gumbel to show effect of SLR, with arbitrarily chosen parameters

Failure mechanisms are another important factor when assessing the risk of flooding in a project area. A failure mechanism refers to the potential ways in which flood protection measures could fail. The breaching of a levee is an example of a failure mechanism. By identifying all the failure mechanisms, an accurate flood risk assessment can be performed. Once the protection level and failure mechanisms have been defined, probabilities (or return periods) can be assigned to flood events or inundation levels.

4.1.2. Potential Damage

The second component of risk, concerns the potential impact that a flood could have on people, property and infrastructure. As discussed earlier, only tangible direct damages are included in this thesis. Whether loss of life is considered as a tangible differs per literature source. J. Kind (2011) for example, propose a framework in which loss of life is monetarily valued, however Slager and Wagenaar (2017) and Kok, Huizinga, Vrouwenvelder, and van den Braak (2005) qualify loss of life as intangible. The latter approach is used for this thesis. To model the total of physical damages in a flooded area, Equation 4.4 as described in (S. N. Jonkman et al., 2008) is used.

$$D = \sum_{i}^{m} \sum_{r}^{n} \alpha_i \left(h_r\right) D_{\mathrm{max},i} n_{i,r} \tag{4.4}$$

In which:
D_{max} [-] = maximum damage amount for an object or land use category i;
i [-] = damage or land use category
r [-] = location in flooded area
m [] = number of damage categories
n [] = number of locations in flooded area
h_r [-] = hydraulic characteristics of the flood at a particular location
$\alpha_i(h_r)$ = stage-damage function that expresses the fraction of maximum damage for category i as a function of flood characteristics at a particular location.
$n_{i,r}$ = number of objects of damage category i at location r.

Damage curves can be used to estimate the potential damage that could occur at different inundation levels Figure 4.4 shows the damage fractions for different inundation levels, varying per land-use type. With the fraction and the land-use value, the curves can be transformed to costs for different inundation levels.

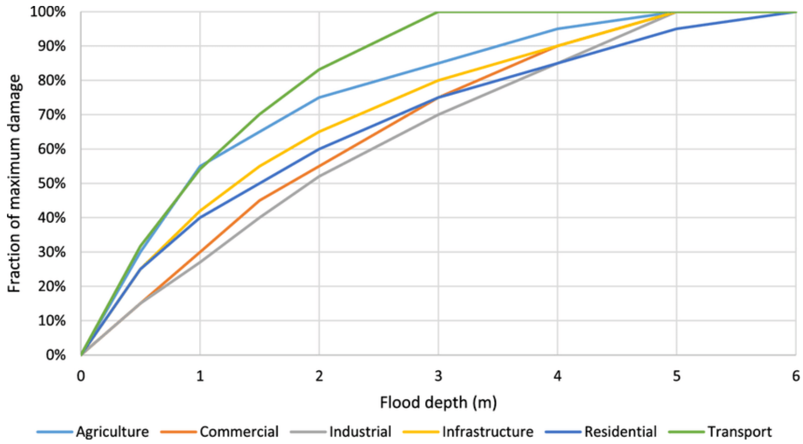


Figure 4.4: Damage curves by (Huizinga et al., 2017). Every colour represents a different land use type. The fraction of damage is plotted per flood depth.

4.1.3. Flood risk without measure

At this point, all factors required to determine the flood risk and how this will increase over time are defined. To calculate the annual flood risk, a probabilistic approach is used. This involves analysing the probability of different flood scenarios for different return periods and estimating the potential damage that could result from each event. By combining these estimates, the annual flood risk can be determined and how this may change over time. For this calculation, Equation 4.5 is used. As the sea level rises continuously, the annual risk changes for every year.

$$\text{Annual Risk} = \sum_{p=1,10,100,..}^{P} \left(\frac{1}{P_p} - \frac{1}{P_{p+1}} \right) * \frac{D_p + D_{p+1}}{2} \tag{4.5}$$

In which:
Annual Risk [€/year] = Expected Annual Risk in year t
P [years] = Return period of a certain water level
D [€] = Expected associated damages of certain return period

4.2. Section B: Characteristic of the flood risk reduction strategies

The second section focusses on all the factors related to a flood risk reduction strategy. The section starts with defining different strategies, and ends with defining the associated costs and describing the impact on the flood risk.

4.2.1. Define flood risk strategies

For this research, it is crucial to articulate both static and adaptive strategies. The goal of this research is to explore the integration of flexibility into the economic assessment of adaptive planning. Therefore, different type of strategies are required to facilitate a comparative analysis between the strategies.

Annual Risk with measure

The implementation of a flood risk reduction measure is supposed to reduce the annual flood risk. The measure can either change the probability of a flood event, or it can reduce the amount of damage in case of a flood event. The same equation used for the annual risk without measure can be applied (see Equation 4.5), however, this time with updated input values. Once the annual risk with the implementation of the measure is the determined, the benefit of the measure can be calculated, see Equation 4.6.

$$B_{PV} = \sum_{t=1}^{T} \frac{R_{t,nm} - R_{t,m}}{(1+r)^t} \tag{4.6}$$

In which:
T [yrs] = Time horizon
B_{PV} [€] = Present Value of benefits of implemented measure during lifetime
$R_{t,nm}$ [€] = Risk in year t when no measure is implemented
$R_{t,m}$ [€] = Risk in year t when measure is implemented
r [-] = Discount factor

Initial Investment Costs

The implementation of a flood risk reduction measure requires an initial investment that includes both fixed and variable costs. The fixed costs are one-time costs incurred for the design and preparing the construction site, for example. The variable costs or depended on the dimensions of the measure.

Operation and Maintenance Costs

In addition to the initial investment costs, the implementation of a flood risk reduction measure also incurs ongoing Operations and Maintenance (O&M) costs. These costs are associated with maintaining and operating the measure over its lifetime. The OM costs depend on the type of measure implemented and the level of maintenance required.

So, costs of a measure consist of the initial investments costs, made at the start of the measure, and the O&M costs which are costs made during the rest of the measure's lifetime. As the costs are made at different moments in time, the costs have to be discounted. According to S. Jonkman and Steenbergen (2015), the costs are determined as follows:

$$C_{PV} = \sum_{t=1}^{T} \frac{OM}{(1+r)^t} + I \tag{4.7}$$

In which:
C_{PV} [€] = Present value of the measure costs
I [€] = Initial investment costs of measure
OM [€/year] = Operation and maintenance cost of measure

However, when measures with different lifetimes are considered, the NPV does not result in a value that can be used for a fair comparison. To overcome this problem, the concept of the Equivalent Annual Costs (EAC) can be used. This is a financial concept which is often used for capital budgeting decisions. This method enables the comparison of the cost-effectiveness of assets with unequal lifespan (Newnan et al., 2004). Schoemaker et al. (2016) earlier applied this concept to flood risk reduction strategies. Important to note that as the NPV is used, a positive EAC value implies benefits. In this formulation, the higher the EAC, the better. The following formulas are involved in this concept:

$$EAC = \frac{NPV}{A_{t^*,}} \tag{4.8}$$

In which the annuity factor is calculated as follows:

$$A_{t^*,i} = \sum_{t=1}^{t^*} \frac{1}{(1+r)^t} = \frac{1 - \frac{1}{(1+r)^{t^*}}}{r} \tag{4.9}$$

In which:
r [-] = Cost of Capital / discount rate
t [years] = number of years of entire lifespan

4.3. Section C: Cost Optimal Measure

Flood risk management strategies require careful consideration of the height of flood risk reduction measures, such as levees or flood walls, due to their impact on costs and effectiveness. Higher measures provide increased protection against flooding and subsequently reduce the risk of damage to infrastructure and property. However, beyond a certain point, the marginal benefit of additional height decreases, resulting in a non-linear relationship between the height of the measure and risk reduction.

The cost of constructing and maintaining flood risk reduction measures also increases with height due to additional materials and engineering requirements, and land acquisition and maintenance costs. In contrast, higher measures may have a longer lifespan than lower measures, as they can withstand larger floods and are less likely to be over topped or breached. The maximal functional lifetime of a measure has to be taken into consideration as well, when determining the optimal measure height. The end lifetime of the measure is either determined by the moment the minimal required safety level is reached or when the functional lifetime of the measure has been exceeded. The determination of the minimal required risk for an area, concerns a thorough risk assessment. In this assessment, the consequences are quantified. The Expertise Network on Flood Protection (ENW) prescribes to include the assessment of both individual, societal and economic risk. For this research, the determination of the minimal required safety level is out of scope. It is assumed that the minimal required safety level is already known at the start of the project.

When a measure is build, the initial protection level reduces overtime. This can be caused by different factors, like functional performance, but also different climate conditions can result in lower protection levels. In the example below, it is assumed that only SLR contributes to the decrease of the protection level over time. As described above, the initial protection level of a measure can be economically optimized. The NPV metric is commonly used to assess the economic feasibility. The optimal height of a flood risk reduction measure is determined by balancing the benefits of reduced flood risk with the costs of construction and maintenance over its lifetime, maximizing its NPV. Figure 4.5 shows an illustration of the economic optimization concept. A certain measure-height corresponds with a certain protection level, these terms might be used interchangeably.

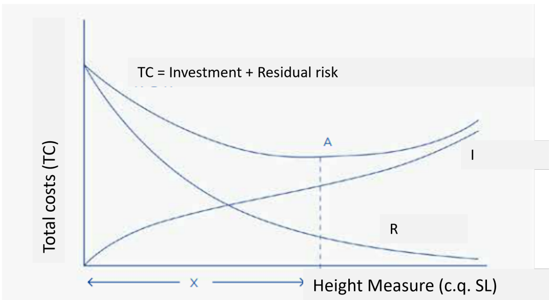
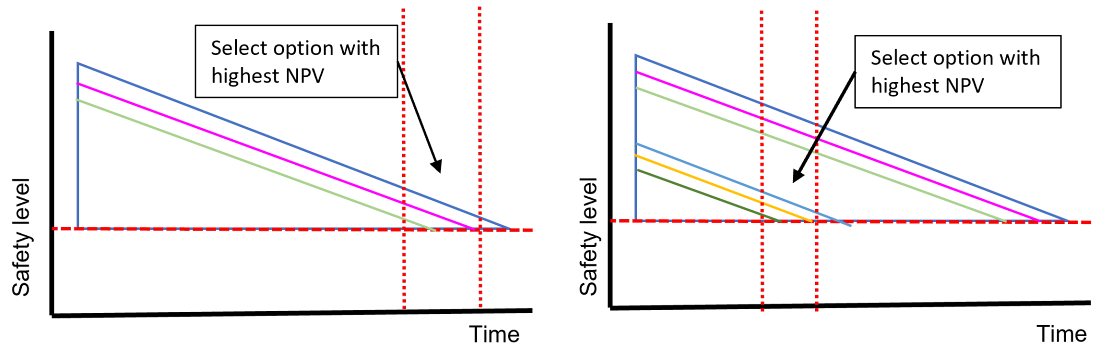


Figure 4.5: Illustration that visualizes the concept of determining the optimal measure height (x-axis) whilst minimizing the total cost. - adjusted(Kok et al., 2016)

4.3.1. Static strategy (1-step)

In Figure 4.6, a schematization is provided to illustrate the determination of the optimal protection level. In the schematization, different safety levels (c.q measure heights) are tested, the cost optimal height, or protection level then defines the end of the measure lifetimes. In Figure 4.6a, three different heights (c.q protection levels), are plotted. The safety level decreases overtime and stops when the dotted red line is reached, which illustrates the minimal required safety level. The rate, of the safety level decrease, is determined by the SLR-rate that is considered. When, for an example, a faster rate is considered (higher SLR-scenario), the safety level will decrease quicker. In the figure, this would be visible by a steeper slope.

The height, that returns the highest NPV is selected. The vertical dotted lines illustrate a timeframe which can be defined in case a projected lifetime of a measure/strategy is set.



(a) Optimal SL **(b)** Optimal safety level 1 measure for adaptive strategy

Figure 4.6: Determining optimal SL, every colour represents a different measure height and therefore a different initial protection-level.The height that results in the highest NPV, is the cost optimal measure height.

4.3.2. Adaptative Strategy (two-step)

In case of an adaptive, flexible strategy, the first measure height will not be based on cost optimization. In Figure 4.6b, Figure 4.6a has been adjusted. In Figure 4.6b, the same concept is depicted, but then for an adaptive strategy which starts with a smaller step. In this way, an extra 'decision moment' is created in the project horizon. A smaller step means a shorter expected lifetime of the measure. Therefore, the first measure height will be lower, and reaches the minimal required safety level sooner. Again, if a time frame is set (vertical lines), the selection will be based on the height that ends within this timeframe. This timeframe can be chosen arbitrarily, keeping in mind that enough time has passed to be able to experience benefits from reduced uncertainty. However, when postponing this moment too long, the concept of 'being able to react' on how the future unfold diminishes. The second measure will then be determined in such a way that it will reach the defined project horizon. So, for example, for a static strategy, the optimal height could be 2m, with an associated projected lifespan of 100-years. For an adaptive strategy, first the optimal height (1m) is determined for a projected lifespan of 50 years. Subsequently, when the measure of the adaptive strategy no longer meets the minimal protection requirement, a new optimal height is determined based on the newly acquired data.

4.3.3. Impact of SLR on the optimal measure

For the determination of the optimal protection level, an initial SLR scenario was assumed. However, the rate of SLR is subject to uncertainty, so there is no guarantee this initial assumed SLR occurs. Therefore, two measure heights are determined for the 2nd measure; one in which the assumed initial SLR scenario turns to occur and one in which the assumed scenario turns out differently. In Figure 4.7 this principle is schematized. Initially, the first measure was based on a here called 'low' scenario. The 'low'- scenario assumption can turn out to be adequate. However, in case of a 'high' scenario, the minimum required safety level is reached earlier and subsequently the height of the second measure should be higher than for the initially assumed scenario. This process of scenario-based determination of measure heights, can be repeated as many times as SLR-scenarios are included. The just described process can be repeated starting off from an assumed 'high' scenario, for example. In this stage, all the input variables, like the SLR, the economic growth or the investment costs, are considered to be deterministic. However, in reality these values are stochastic values and therefore come with uncertainty distributions. In the final section, uncertainty was included for the economic evaluation.

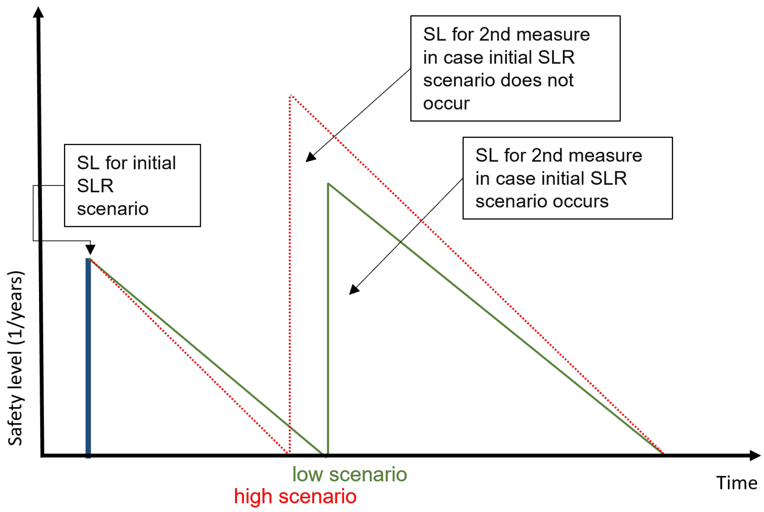


Figure 4.7: Cost Optimal safety level for two scenarios

4.4. Section D: Economic performance evaluation

In this section, the method to perform an economic evaluation of the strategies is described. The formulated strategies are tested for 'all possible' futures, which means uncertainty in taken into consideration. This is done by performing a MC-analysis. In Figure 4.14, a flowchart in which the steps for a single MC-run are shown, is provided. For the sake of accuracy, it is important that the same set of 'futures' (combination of sampled variables), are used to evaluate every strategy. In this research, Python is used as programming software. Within this software, a so called 'seed' can be defined to ensure this. The MC-analysis is used to calculate different economic performance indicators. Subsequently, these parameters serve as tool to analyse individual strategies and compare the strategies with each other.

4.4.1. Define uncertainties

As many as preferred stochastic variables, with corresponding uncertainty distributions, can be defined. The framework is constructed for minimal one uncertainty to be included, which is the SLR. Below, the impact of the uncertainty of SLR for a MC-run is discussed.

Sea Level Rise

The first step in the MC analysis concerns defining the included SLR scenarios. It is important to note that the scenarios themselves do not represent probabilities of occurrence. Rather, they are designed to explore a range of plausible futures under different assumptions about socio-economic development and policy choices. The probability of the scenarios occurring is not known and may depend on many uncertain factors such as technological progress, political decisions, and societal values (Pörtner et al., 2022). It is often considered as a political choice which scenario is taken into consideration for projection of future climate risk. The number of SLR-scenarios taken in to consideration remains open and can be decided per case study. Furthermore, one can decide which probabilities are assigned to each SLR-scenario, in case multiple are in scope.

Defining a distribution that describes the trajectory of SLR is complex. For this research, IPCC data is used, as these projections are used and accepted globally. Per scenario, the IPCC has defined the mean SLR for every 10 years until 2150. For every time step, the 16th and 83rd percentile values are defined to quantify the bandwidth. For the years in between, it is common to assume a linear behaviour and therefore interpolation can be used. What becomes clear from the data, and which is also visible when looking at the visual representation of the SLR projections, is that the absolute variance of the SLR increases over the years. In Figure 4.8, a plot of the SSP1-2.6 trajectory is plotted, in which the increasing absolute variance is clearly visible. In theory, for sampling a SLR-trajectory, one can sample the amount of SLR for every time step, based on the distribution for that time step, and then interpolate for years in between to generate the entire trajectory. However, in this way, no correlation between the years is included.

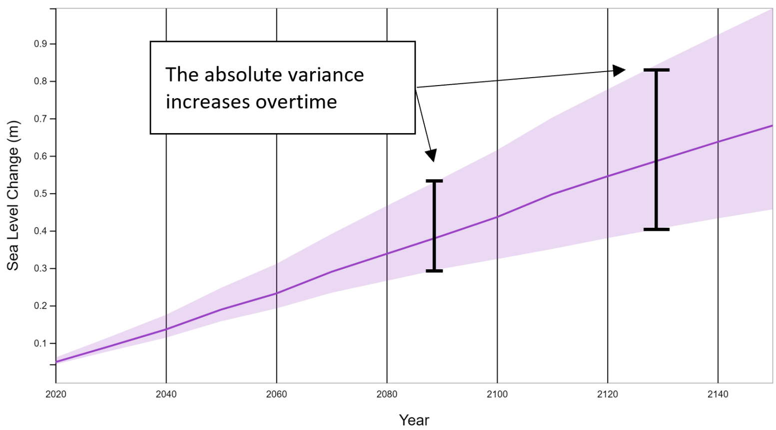


Figure 4.8: Sea Level rise projection for scenario SSP1-2.5. This figure illustrates how the absolute variance increases overtime (IPCC, 2020) - adjusted

In practice, this can imply that first the amount of SLR is sampled in the higher quantiles but 10 years later, a sample in one of the lower quantiles is sampled. In many studies different approaches were found, some only sample for a single time step and inter- and extrapolate for the years in between, like done by de Ruig (2020) and Trommelen (2022). For this research, a different approach has been thought of. A so called SLR factor is introduced. This is a stochastic value and based on this single value, the entire trajectory can be defined. The SLR-factor is normally distributed with a mean (μ) of 1. The standard deviation can be fitted through the IPCC data points. So for example, when a SLR-factor of 1.2 is sampled, the mean SLR for the incorporated time steps are multiplied with this factor. The use of this factor guarantees the correlation between the different time steps, and results in an increasing absolute variance of the years. In Figure 4.9, the method is schematized.

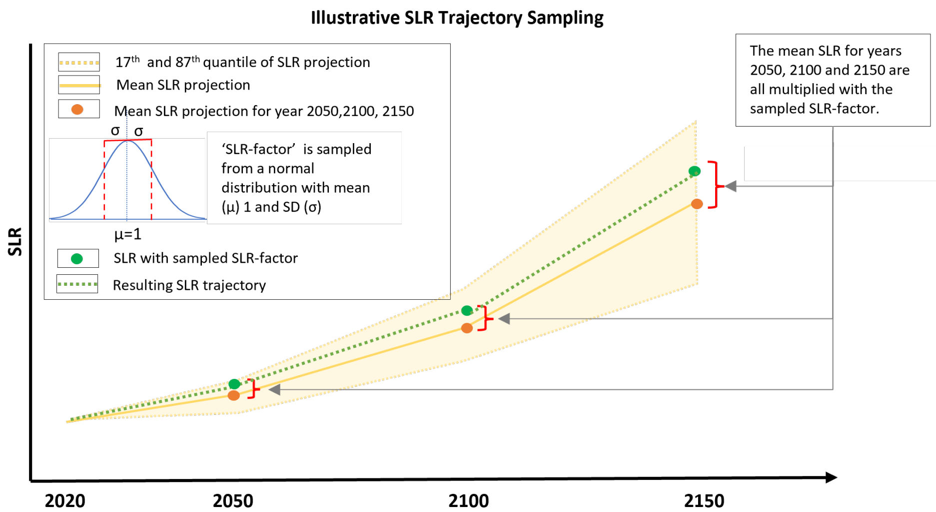


Figure 4.9: Illustrative schematization of the sampling method of the SLR-trajectory. From a normal distribution, the SLR-rate is sampled. The mean values for the included time steps, are multiplied with the sampled SLR-factor. Interpolation in used to define the trajectory for the intermediate years.

Impact SLR on second measure with 'extra knowledge'

In Section 4.3, it was explained how the height for the first step and if applicable, two potential heights for the second measure were determined (based on which SLR-scenario appears to be happening). The end of the first measure is determined by the actual amount of SLR. In case of a second measure, the actual occurring SLR determines the height of the next measure. The height of the second measure were based on the mean SLR for the included scenarios.

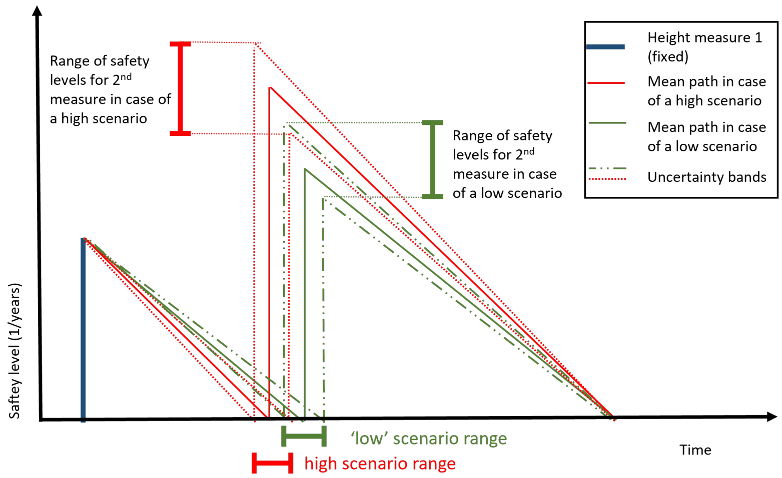


Figure 4.10: Cost optimal measures with ranges due to uncertainty. The dashed lines illustrate the bandwidth of the trajectories of the safety level. The bandwidths are the result of the uncertainty of the SLR.

However, as just explained, within a scenario, an uncertainty band exists. Figure 4.10 schematically gives an overview of the situations that can occur. In the example, a strategy starts with implementing a measure with a height determined as explained in Section 4.3. Then, based on the actual SLR, the safety level will decrease. The green and red solid line represent the mean 'low' and 'high' paths. The dashed lines, represent the uncertainty bands for both scenarios. As visualized, the height of the second measure should adjust accordingly. The sampled 'SLR-factor', can serve to adjust the earlier defined height. In Figure 4.11, this method is schematized.So, for example the sample '1.2' is sampled from the 'low'scenario', the rate is 1.2 'stronger' than the mean rate, following that the height of the second measure should be 1.2 higher than the initially determined height. The same holds when the rate is slower than the mean, in that case the height can be lower as well.

The limitation of this method, is that in this way, it is assumed that the actual SLR can be determined exactly. This would result in an unrealistic level of precision in the determination of the height for the second measure. To overcome this aspect, a second 'SLR-factor' is sampled, which describes the SLR after the decision moment. For the projection of the SLR after the decision moment, more observations have become available. The experienced SLR, until the decision moment, is indicative for the expected SLR for the years after the decision moment. So, in case of the model, the SLR-factor for the 2second time period is correlated with the first sampled SLR-factor. So, if for the first time step, a strong rate (c.q high SLR-factor) was experienced, is it logical to assume this trend will continue for the coming years. In Section 3.2, it was concluded that no evidence was found that the uncertainty of SLR will reduce. Therefore, in this research, it is assumed that the uncertainty remains the same. Implying that, when for example looking in 50 years at the uncertainty range for the subsequent 50 years, the same absolute variance is assumed as the projection today for over 50 years. For clarity, this principle is illustrated in Figure 4.12.

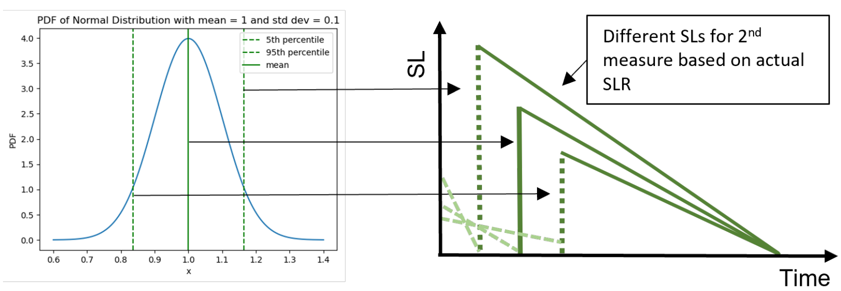


Figure 4.11: Flexible Safety levels that are based on actual, experienced SLR

In the example in Figure 4.12, the first time step is 65 years (2020-2085) and the second time step is 65 years as well (2085-2150). So the projected time is equal, so should be the absolute variance. A SLR-factor of 1.2 is sampled, which is shown with the green dots. Then, starting in 2085, a second SLR uncertainty band is shown, with a mean of 1.2. In this way, the correlation between the two time step is guaranteed. Then the SD is fitted in such a way that, the absolute variance is in 2150 is the same as in 2085. Then, from this new distribution, shown on the right side of the plot; a second 'SLR-factor' is sampled. This factor is then used to determine the height of the second measure.

So to summarize, with the above described method, the uncertainty of the SLR at a decision moment is determined. Instead of tailoring the second measure to the exact SLR-factor, the measure is determined by the SLR-factor sampled from a 2nd SLR-factor distribution. The assumption is made that the absolute variance of the SLR remains the same.

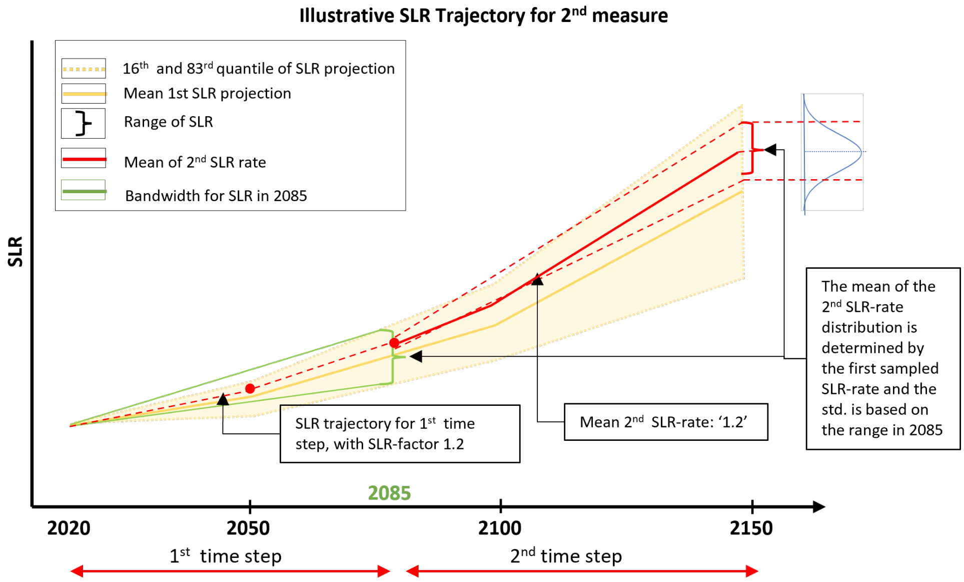


Figure 4.12: Schematization of SLR-factor for 2nd measure. To make the determination of the height of the second measure more realistic, as second SLR-factor is introduced. This factor is sampled for a new distribution and represents the uncertainty of the SLR for the second time step, with the knowledge what has happened in the first time step

The next step involves performing the MC-analysis. Figure 4.14 at the end of this chapter, shows a deep dive into a single MC-simulation. In this figure, various stochastic variables are included, however as mentioned before, this is open to preference.

4.4.2. Economic Performance Parameters

To be able to analyse a single strategy, or compare strategies with each other, performance parameters are defined. In this research, only quantifiable, economical parameters are used for evaluating the strategies. Based on the findings in Chapter 3, the calculation of seven performance parameters is included in the model.

1. NPV
2. BCR
3. Reduced Risk
4. Total Investment Costs
5. EAC
6. Coefficient of Variation (CV)
7. Probability of Loss (PoL)

The first five metrics were already discussed earlier in this section. Below, the Coefficient of Variation (CV) and the Probability of Loss (PoL) are described. Furthermore, the motivation to include them in the framework is discussed.

Coefficient of Variation

When a MC-analysis is performed, a set of results are calculated. The magnitude of the spread of the result is determined by the included stochastic variables. Multiple metric exist that describe the spread of a data set. A commonly used metric is the variance. However, in this analysis the CV is used. The CV and variance are both measures used to quantify the variability within a dataset. However, the methods used to calculate them and the insights they provide are different.

Variance describes how much the data is spread out by calculating the average squared difference between each data point and the mean of the dataset. It is computed by dividing the sum of the squared deviations from the mean by the number of observations minus one. Variance is expressed in the same units as the original data.

$$\sigma^2 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{N-1} \tag{4.10}$$

In which:
σ^2= Variance
x_i = Each value in the data set
$\bar{x}$=Mean of all values in the data set
N= Number of value in the data set

The CV, on the other hand, is a metric of relative variability that shows the standard deviation of a dataset as a percentage of the mean. Equation 4.11 shows how the CV is calculated. Unlike variance, the CV is dimensionless and can be used to compare variability across different datasets with varying scales or units.

$$\text{Coefficient of Variation (CV)} = \frac{\sigma}{\mu} * 100\% \tag{4.11}$$

In which:
σ = standard deviation
μ = mean

The CV plays a role by providing a standardized measure of variability, enabling meaningful comparisons between datasets with varying means and units. For instance, when to two datasets of NPVs are considered: one with a mean of 50 and a standard deviation of 10, and another with a mean of 100 and a standard deviation of 20. Although both datasets have different means and standard deviations, their CV values can be compared. In this case, the CV of the first dataset would be 20% (10/50 * 100), while the CV of the second dataset would also be 20% (20/100 * 100). This allows for the relative variability of the datasets to be compared accurately, highlighting their relative dispersion regardless of their different scales or units.

By utilizing the CV, decision makers can effectively evaluate and compare the variability of outcomes, even when the means and units differ. It provides a standardized metric that captures the relative spread or dispersion of the data, allowing for a better comparison and insights into the variability between datasets and therefore the performance of the strategies.

Probability of Loss

The above described performance parameters tell a lot about the economic performance of a strategy. However, caution is required because relying on the highest NPV can result in a distorted view. When solely, the mean NPV is considered, there is a chance that is interesting insights are missed. In Figure 4.13 shows an example of a probability and cumulative distribution function for two different strategies. Based on the highest mean NPV, strategy ’A’ is preferred. However, when the results are plotted in the cumulative distribution function, one can argue whether strategy ’A’ is still the preferred strategy as there is a much higher chance of a negative NPV.

The Probability of Loss (PoL) is a financial metric that is used to evaluate the potential financial impact of an investment. Specifically, it represents the probability that the NPV of a flood risk reduction investment will be negative. The higher the PoL, the less the performance of the strategy.

$$\text{Probability of Loss} = \frac{\text{Number of outcomes of NPV} < 0}{\text{Total number of samples}} \times 100\% \tag{4.12}$$

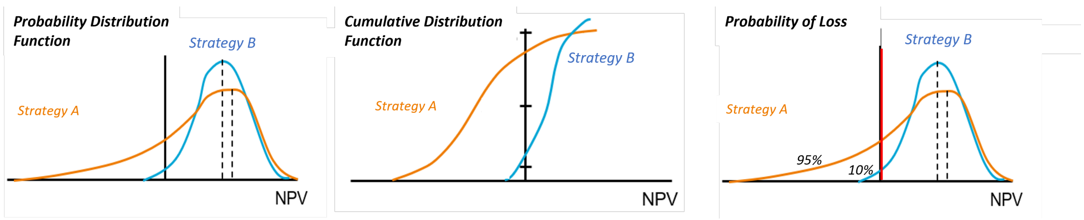


Figure 4.13: Illustration of a distorted view. This schematization is used to emphasize the importance of the PoL metric. When only looking at the highest NPV, important insights can be missed

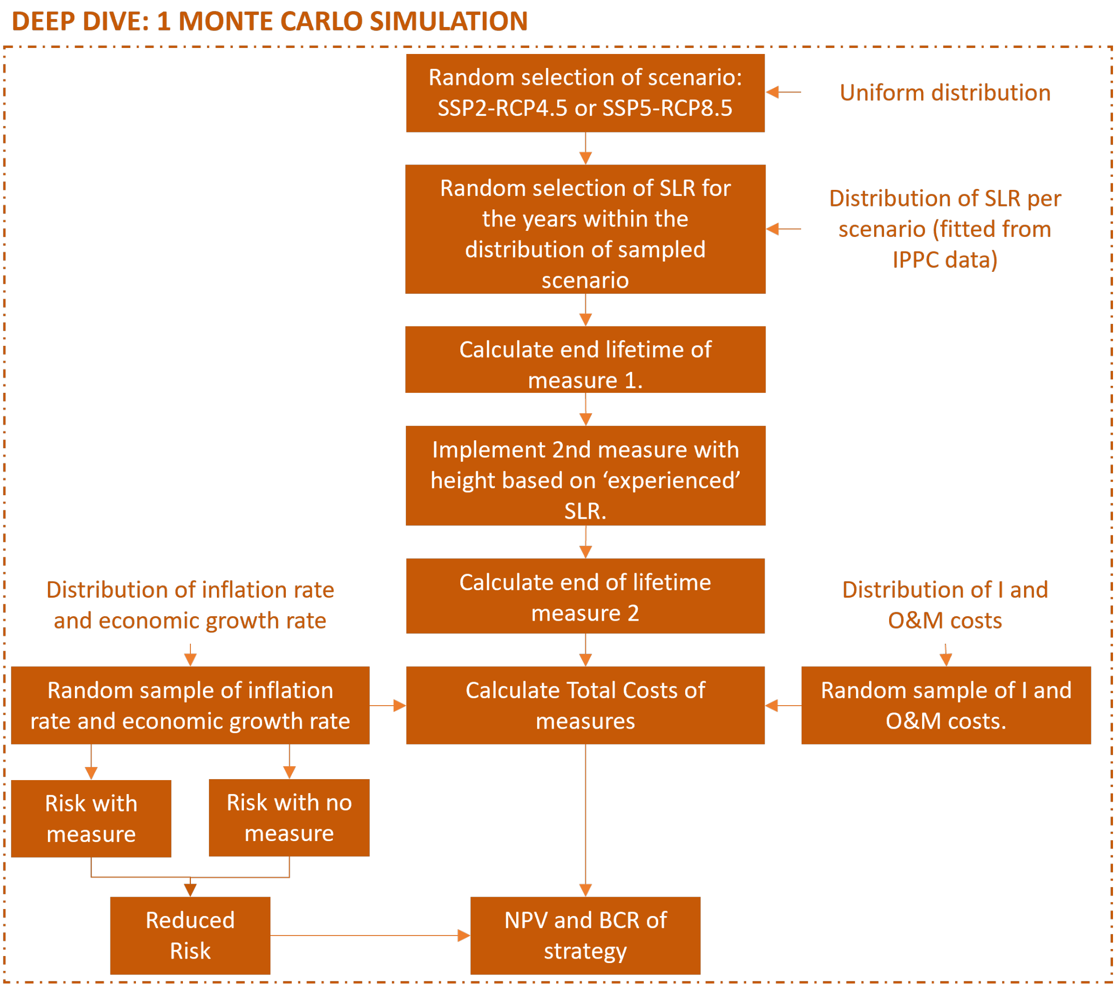


Figure 4.14: Deep dive Monte Carlo Analysis

5
Conceptual Case Study

In this chapter, the framework described in the previous chapter is tested for a conceptual case study. The same structure of the framework is used, meaning that this chapter is divided into four sections. The Python code can be found in Appendix C

A. **Project Area Characteristics**

B. **Specification of Adaptation Strategies**

C. **Cost Optimal Measures**

D. **Economic Evaluation**

The site characteristics of the conceptual project area are described in Section 5.1. Then the different strategies that are evaluated are described in Section 5.2. This involves defining the associated costs and how the measure reduces the flood risk. Next, in Section 5.3 the optimal measure height for the different measures are defined. The chapter ends with Section 5.4 in which the results of the conceptual case study, uncertainty test and four sensitivity tests are discussed.

5.1. Section A: Project Area Characteristics

To test the framework, a conceptual project area is defined. A residential area is evaluated with a rectangular geometry; 150 m x 300m. The land is connected to the sea by a stretch of 150m. The connection with the sea forms the driver of the flood risk. It is assumed that the area, outside the project area, experiences no coastal flood risk. In case of the measure flood proofing is applied, 20 houses are in scope. At the start of the project, no measures are in place yet. In Figure 5.1 a schematic map of the project area is provided.

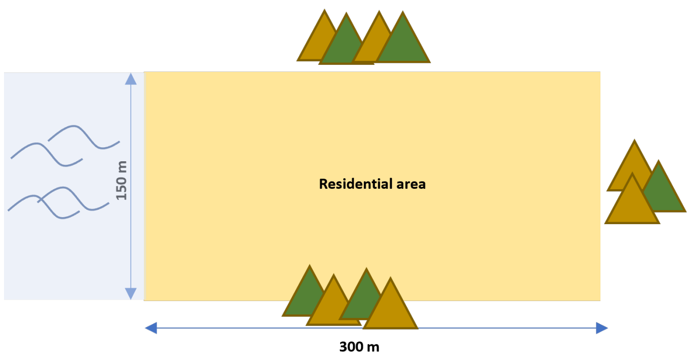


Figure 5.1: Map of conceptual case study area. The stretch of land connected to the sea is 150 meters. The area outside the project area is out of scope for the analysis as it is elevated (mountainous area) and therefore subjectable to coastal flood hazards.

5.1.1. Probability of Flooding

To determine the current flood risk for the project area and how this risk will evolve overtime, the probability of flooding is determined first. This is composed of three factors, the extreme water levels, the SLR projection and the current safety level, which are discussed individually below.

Extreme Water Levels

To model the extreme water levels, a Gumbel distribution with a scale parameter of 0.5 and a location parameter of 2.8 is used. In Figure 5.2, return periods with the corresponding water levels for the conceptual project location are shown. Additionally, the situation in which the sea level has risen with 0.5m has been included in the plot.

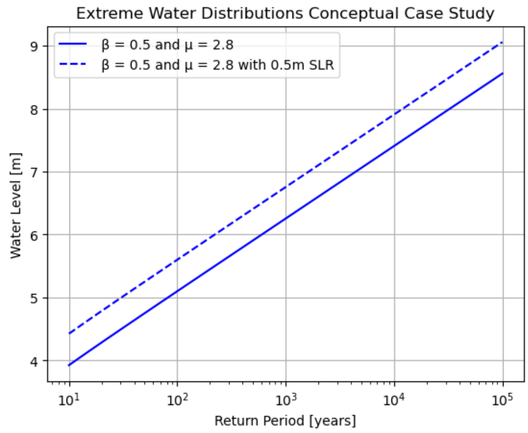


Figure 5.2: Extreme Water Levels per Return Period for the conceptual case study area. The dashed line shows the situation in which the sea level has risen with 0.5m.

Sea Level Rise Scenarios

For the conceptual case study, two IPCC scenarios are used: the SSP2-4.5 and the SSP5-8.5 scenario. The SSP2-4.5 as 'the middle of the road' and the SSP5-RCP8.5 and the more extreme scenario, as described in the AR6 report of the IPCC (Pörtner et al., 2022). SSP2-4.5 is a scenario that assumes moderate mitigation efforts to reduce greenhouse gas emissions, which would result in a peak in emissions in the mid-21st century, followed by a gradual decline. It is therefore considered as a medium GHG emissions scenario. The SSP2-4.5 scenario assumes a world with a balance between economic development and environmental sustainability. SSP5-8.5, on the other hand, is a scenario that assumes a lack of mitigation efforts and continued high greenhouse gas emissions. It is therefore considered a high GHG emissions scenario. SSP5-8.5 assumes a world with a focus on economic growth and increasing fossil fuel use. The projections of the included SLR-scenarios are shown in Figure 5.3.

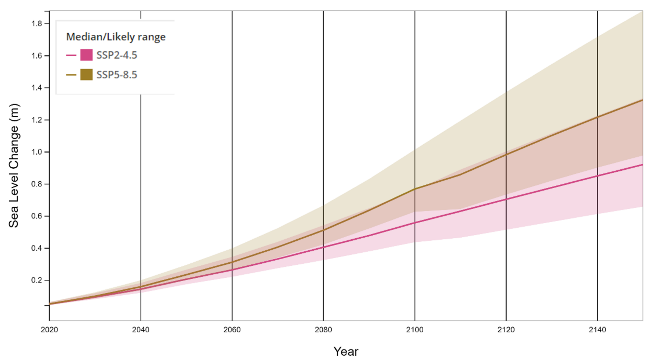


Figure 5.3: Projections of the Sea level rise scenarios that are included for the conceptual case-study. (Pörtner et al., 2022)

Table 5.1: Fitted SD of the SLR-factor. This factor is sampled from a normal distribution and determines the trajectory of the SLR. The SD that was found is 0.38 for both scenarios. The SLR for the trajectory is constructed by multiplying the sampled SLR-factor with the mean values from the IPCC.

Quantile	**SLR-factor**	**SLR:**	**2040**	**2060**	**2080**	**2100**	**2150**
SSP2-4.5	[-]		[m]	[m]	[m]	[m]	[m]
Fitted 16th	0.62			0.16	0.25		0.57
16^{th} **-IPCC**				**0.22**	**0.32**		**0.66**
50th **- IPCC**	**1**		**0.14**	**0.26**	**0.40**	**0.55**	**0.92**
83rd **- IPCC**				**0.34**	**0.54**		**1.33**
Fitted 83rd	1.36			0.36	0.55		1.25
SSP5-8.5							
Fitted 16th	0.62			0.19	0.32		0.82
16th **-IPCC**				**0.26**	**0.42**		**0.92**
50th **-IPCC**	**1**		**0.16**	**0.31**	**0.51**	**0.77**	**1.32**
83rd **- IPCC**				**0.40**	**0.66**		**1.88**
Fitted 83th	1.36			0.42	0.69		1.80

As described in Section 4.4.1, a so called SLR-rate factor is defined to model the projections. The SLR-rate factor is a stochastic variable which is assumed to be normally distributed. The mean of the distribution is set to 1, the standard deviation (SD) is fitted based on the data for the 16th and 83rd quantiles of the projection. For the two scenarios, the same SD was found: 0.38. In Table 5.1, the used data points for the two SLR-scenarios are listed. Additionally, the results of the calibration of the SD for the SLR-factor can be found.

For the modelling, a normal distribution was assumed, which implies boundaries from $-\infty$ till ∞. In practice, this will result in unrealistic results. For this reason, upper and lower boundaries were defined at the 5th and 95th percentile, corresponding with the IPCC data. As can be seen in Table 5.1 the deviation from the fitted distribution and the actual data, the uncertainty range of the SLR-rise projection doesn't follow a normal distribution. The absolute uncertainty, for the lower part of the projection is smaller than for the upper range of the projection, therefore either the 16th or the 83rd-quantile will fit best to the distribution. In the used distribution, the fitted data deviates more for the 16th quantiles than for the 83rd.

In Section 4.4.1, the method to project the SLR for the period after a decision moment, so for an adaptive strategy, is discussed. For SSP5-8.5, the SD for the second time step was determined to be 0.23. In Figure 5.4, the results are shown. For example, when the first time step last until 2085 a spread of 0.47m was found (65 years). Then in 2150, starting in 2085, approximately the same value, 0.45m is found. In case the time step is shorter, until 2065 for example (orange point), the variance for 2150 is greater. The time between 2065 and 2150 CVers 85 years. So, the absolute variance of 2105 is used as reference, as this is 85 years from 2020. In 2105 the absolute variance is 0.63m, which is also found in the year 2150. The same SD was found for SSP2-4.5.

In Chapter 2 it was discussed that the IPCC has not defined probabilities for a single scenario. For this conceptual case study, the probability of the individual scenarios, is assumed to be equal, or 'uniform'. So, in other words, the chance that for a MC-simulation either a trajectory within the SSP2-4.5 or the 'SSP4-8.5' is used, is 50/50. Once the scenario is sampled, the uncertainty band for this specific scenario is used to determine the actual sea level rise.

Current Safety Level

The current safety level of the conceptual project location is set to 1:10 per year. To model this, the elevation of the conceptual project area is set to the corresponding water level with a return period of 10 years, which is +3.92m NAP. The current safety level is therefore below the minimal required safety level, which was set to 1:100 per year. Therefore, flood risk reduction measures have to be implemented. It was assumed that the minimal required safety level doesn't change over time.

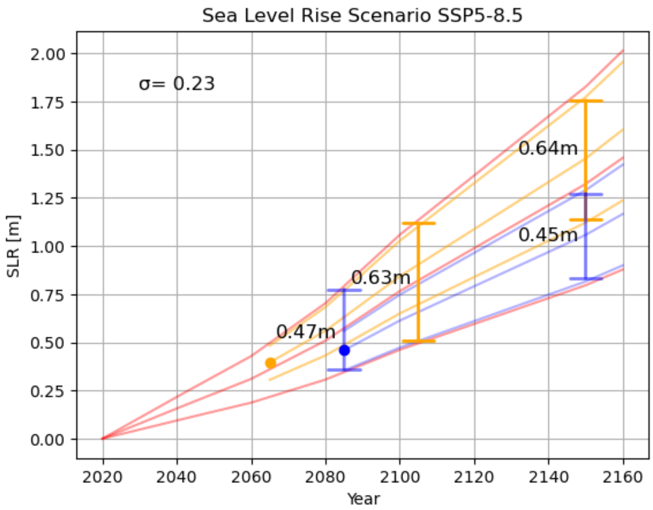
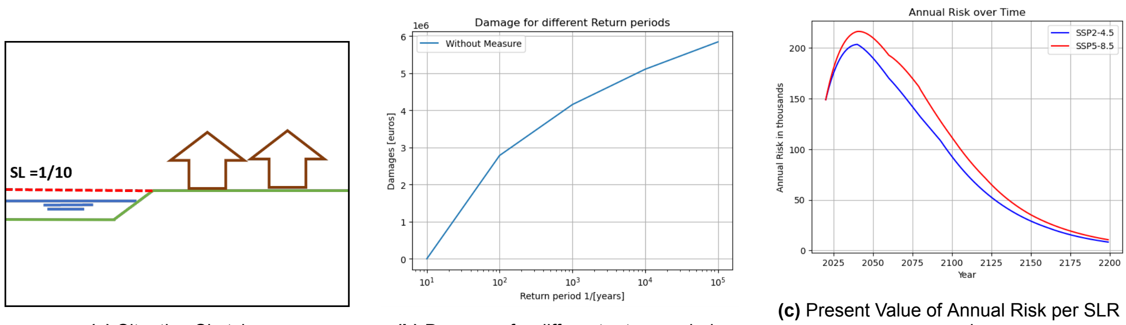


Figure 5.4: Schematization of the fitted SD for the second SLR factor. When more time is passed, the absolute variance is 2150 will be smaller. For the blue variant, a first time step of 2020-2085 and second time step 2085-2150 is considered. For the orange variant, the first time step is between 2020-2065 and the second 2065-2150.

In Figure 5.5a, a schematized situation sketch is given. In case measures are installed, flood-events could occur due to multiple types of failure mechanisms. For flood defences, the probability of flooding is determined by the probability a measure fails. A flood defence can fail due to for example overflow or a geotechnical failure mechanism (e.g. piping or macro-instability). In this analysis, it was assumed that failure due to overflow is the only failure mechanism, assuming that the other failure mechanisms are negligibly small. The same assumption was made in the research of Lendering et al. (2020). The failure mechanism of measures, which are not flood defences, are described individually later in Section 5.2.



(a) Situation Sketch **(b)** Damages for different return periods **(c)** Present Value of Annual Risk per SLR scenario

Figure 5.5: Input variables of conceptual project area. a) a situation sketch of the project area; the land elevation is equal to the current safety level. b) the damages for different return periods. c) a plot of the present value of annual risk in which the impact of SLR and economic growth is included.

5.1.2. Potential Damage

Multiple flood damage curves exist that can determine direct economical damage. To obtain the expected damages for different return periods, the Dutch damage function for residential land-use that were derived by Huizinga et al. (2017) are used. These flood damage curves have been used in a variety of applications around the world and have been cited in numerous scientific publications and reports. For example, his functions were used in the Global Assessment Report on Disaster Risk Reduction published by the United Nations Office for Disaster Risk Reduction (UNDRR) to estimate global economic losses from floods(for Disaster Risk Reduction, 2022).

Although Huizinga's flood damage functions have gained global acceptance, it is worth noting that they were developed based on data from the United States. Therefore, they may not be universally applicable to other regions or flood types. It is often necessary to create region-specific flood damage functions or to adapt the existing functions to local conditions to achieve accurate estimations of the potential impacts of floods in a given area. However, as it concerns a conceptual case study, this was not considered as a problematic factor.

The maximum expected damage is set to $130€/m^2$. For the project area, it is assumed that the land-use will not change during the project lifetime and will therefore be valid for the entire project. Figure 5.5b shows the damages associated to different return periods. As used for infrastructure projects in the Netherlands, a discount rate with a value of 4% is used (Eijgenraam et al., 2000). The average inflation rate of the past century (2010 – 2020) is used, which was 2%. Finally, a socio-economic growth rate of 1% which is based on the GDP growth. In Table 5.2 the used input variables are summarized.

The final step for this section is defining the annual risk overtime in case no measures are implemented. The rate of SLR determines how the risk in the future will evolve, therefore the annual risk is plotted for both scenarios in Figure 5.5c. As can be seen, in case of a higher SLR-scenario, the annual risk will increase more rapidly. Despite an increasing risk due to SLR, the annual risk reduces overtime due to the discounting of future cashflow. In the plot, the impact of SLR, economic growth are included as well.

Table 5.2: Table of the input variables for the case study

Input variable	Value
Area Dimensions	150m x 300m
Land-use type	Residential
Max Damage Value	130 €/m^2
Length Levee	150 m
Number of buildings	20
Inflation Rate	2 %
Socio-economic growth rate	1 %
Discount rate	4 %
SLR scenarios	SSP2-4.5 and SSP5-8.5
1^{st} SLR-factor	μ=1, σ=0.38
2^{nd} SLR-factor	μ=1^{st}SLR-factor, σ=0.23

5.2. Section B: Specification of adaptation measures

Different flood risk reduction strategies, that vary in the level of adaptability, are tested. These are described in subsection 5.2.1. Then, the impact of the included measures are discussed in subsection 5.2.2 and the section ends with presenting the costs of the included measures in subsection 5.2.3.

5.2.1. Define the different flood risk reduction strategies

Unlimited different strategies can be thought of, considering the number of possible (combinations of) measures, at different locations and timings. Therefore, to underpin the choice of the strategies, the following aspects were taken into consideration.

- The impact on the flood risk of the included measures should be quantifiable, without the need of new hydraulic modelling.
- To guarantee adequate comparison between the different strategies, the economic parameters should be determined based on similar project horizons. In case the minimum required safety level is not met, extra measures have to be implemented to ensure the project horizon is met.
- The optimal measure is influenced by which SLR-scenario is assumed. As already mentioned in the previous chapter, this decision is a political-influenced decision. Therefore, the strategies are both tested when starting off from a different design approach. Meaning that every strategy has 2 variants, varying in the initial SLR-scenario.

For the analysis, 4 different variants of strategies have been formulated. For every variant, a different initial SLR-scenario is assumed. This results in a total set of 8 strategies that are evaluated. The 4 variants are described below. Important to note that this selection is not exhaustive, and in other studies different measures can be used. The different strategies are described below. The strategies are schematized in Figure 5.6 in the format of an adaptive pathway. After the individual descriptions, Figure 5.7 is provided, in which the individual pathways are explicitly described.

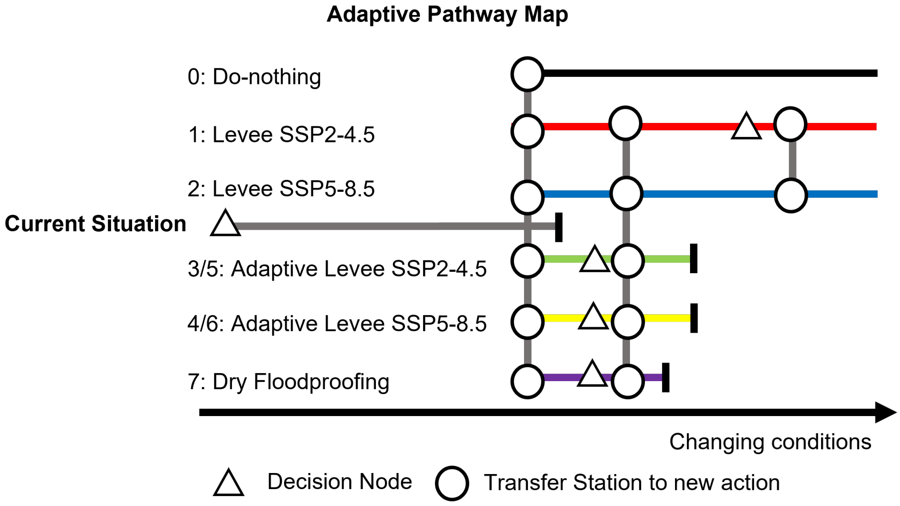


Figure 5.6: Formulated Strategies schematized in a Adaptive Pathway Map. On the x-axis, the changing conditions (SLR) is shown, which determines when a tipping point is reached.

Do-nothing

At first, a 'do-nothing baseline' was examined. In this situation, no new investments in measures are made and the consequences of inundation were solely driven by existing protection measures, natural processes and socio-economic developments. This strategy is referred to as strategy '0' (zero). The outcome of this evaluation, is named the NPV but in this case it is referred to as the value at risk.

Strategy 1 and 2: Static Levee

A static strategy can be described as a 'Decide Once and Build Once' strategy. In this strategy, a levee is built in a single step. This strategy is a so called 'static' strategy because the levee is built with the intention to reach the projected time horizon with one measure. This implies that there is no 'decision moment' in which one can react on how the future is actually unfolding. However, in case the initially stated project horizon is not met, (in case the SLR is faster than anticipated), an extra measure (in this variant the levee should be raised) have to be implemented so that the minimum required safety will be met. In case of overinvestment, the measure will be longer viable than the initially determined projected horizon. For this reason, the EAC metric was included in the set of descriptive performance parameters. This metric enables fair comparison between strategies with different horizons.

Strategy 3 and 4: Adaptive Levee (2-steps)

These strategies are the first adaptive variant and entails building a levee in two-steps. Instead of building a levee which aims to reach the project horizon in one go, the strategy starts with a smaller step. Then, based on how the future unfolds, the second measure can be adjusted accordingly. The first measure depends on which initial SLR-scenario is considered. The height will be lower, when a 'low' scenario is assumed, than when a 'high' scenario is considered.

Strategy 5 and 6: Adaptive Levee (2-steps) with flexibility premium

According to S. N. Jonkman et al. (2013), the unit costs of raising a levee is more expensive than the unit costs of building a levee from scratch. Multiple factors can drive these costs, like the existing levee not being a useful foundation or the extra required space is very expensive to acquire. To take the future cost into consideration, a part of these investments are brought forward.

In this way, flexibility is acquired, which results in a reduction of future potential future costs. In practice, this can be reserving extra land or over designing the initial foundations of the levee. In the study of M.-J. Kim, Nicholls, Preston, and De Almeida (2022), these extra upfront costs are referred to as a 'flexibility premium'. Although no precise values were found in the literature, the values used in this research were determined based on the expert judgement of Professor M. Kok, who was consulted as the expert in this matter. To assign costs to this flexibility, the initial investment will be increased with a flexibility factor. Then, the subsequent measure will then be reduced with the same factor. This strategy, of keeping options open, was inspired on the earlier presented technique in Table 3.1, as it has been in applied is earlier research (H. Liu et al., 2018). Earlier, the two types of options were discusses being real options 'in' and real options 'on' a system. The extra wide and strong fundaments is an example of an option 'in' the system.

Strategy 7 and 8: Flood proofing and levee
In the final strategy, the first measure entails flood proofing the existing buildings. In this way, time is bought to postpone the construction of the levee and therefore gain more knowledge on how the future will unfold. The maximum height of dry-floodproofing is 1.5m (Bignami et al., 2019).

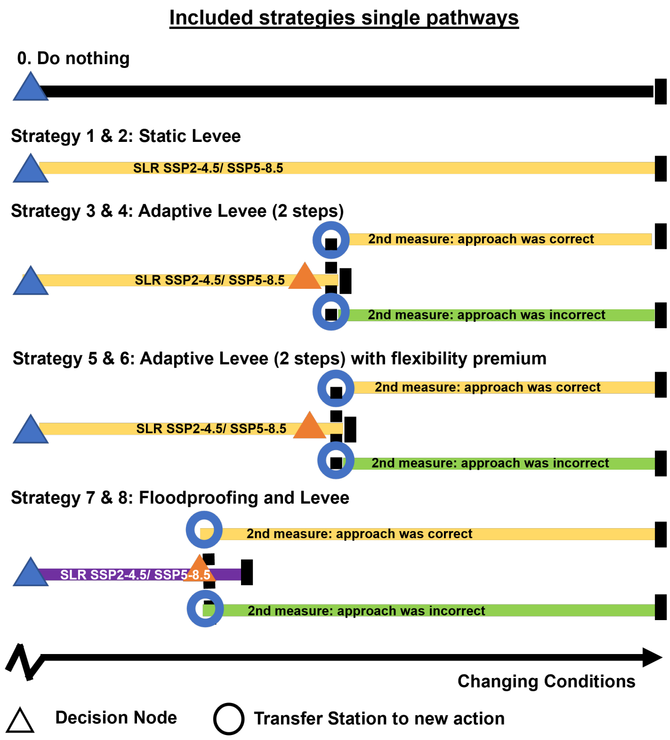


Figure 5.7: Strategies that are tested for the conceptual case. Derived from the adaptive pathway map to explicitly show the different strategies.

5.2.2. Impact of Measure

In the above formulated strategies, two types of measures are included, being a levee and flood proofing. The first mentioned measure influences the probability of flooding, whilst flood proofing reduces the potential damages in case of a flood. The failure mechanism for a levee is overflow, as discussed earlier in section 5.1.1. For Strategy 7 and 8, dry flood proofing is used. This measure makes the building resistant against water up to a certain level. Therefore, when this measure is applied, lower damage costs will be found for the same inundation levels, or return periods. Experience shows that dry flood proofing is not completely watertight, implying a 100% protection. Often an 80% reduction is used in the calculations. In Figure 5.8 these impacts are shown.

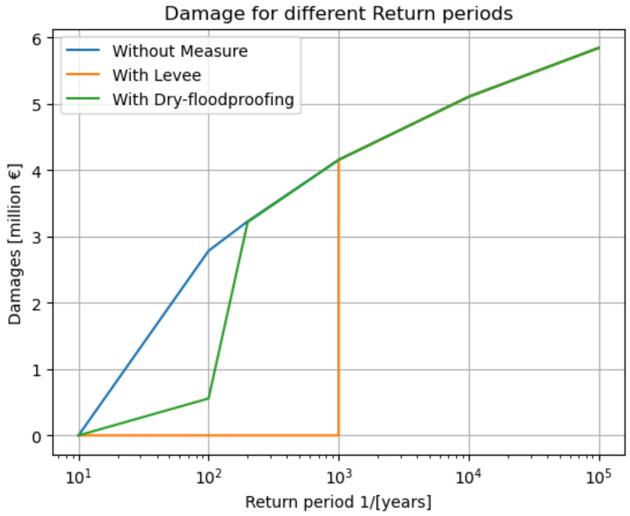


Figure 5.8: The impact of the measures, expressed in the adjusted damages for return periods.

5.2.3. Costs of Measures

The final factor that is discussed in this section are the costs that are associated with the different measures. The costs used for the conceptual case study are shows in Table 5.3. For the calculations, the values are corrected for inflation, using the defined inflation rate.

Table 5.3: Investment and O&M Costs for included measures

Measure	Costs	unit	Source
Levee initial fixed	3	M€/km	Jonkman et al. (2013)
Levee inital variabel	18	M€/m/km	Jonkman et al. (2013)
Raise Levee fixed	3	M€/km	Jonkman et al. (2013)
Raise Levee variable	24	M€/m/km	Jonkman et al. (2013)
O&M Levee	0.2	% per year	Jonkman et al. (2013)
Floodproofing	8700	€/m/building	Aerst (2018)
O&M Levee	2	% per year	Aerts (2018)
Flexibility premium	25	%	(Kok, 2023)

5.3. Section C: Optimal Measure Heights

Once all the strategies, costs and the current flood risk are defined, the optimal measure height were determined. The project horizon was based on the cost optimal lifetime for the static strategy, which was 2150. So in other words, when evaluating different measure heights, the measure with the highest NPV, had a lifetime until 2150 (assuming the mean SLR-trajectory, for the SSP2-4.5 scenario). This project lifetime is then used for the adaptive strategies to determine the measure heights in such a way that the second measure is projected to 'end' in 2150. Or, in other words, reaches the minimal required safety level in 2150. In practice, the cost optimal measure heights, ending between 2150 and 2155 have been used. For the strategies involving dry flood proofing, it was found that for either initial SLR-scenario, the same optimal flood proofing level was found, being the maximum height based on construction limitations (1.5m). From this point on, only a single strategy for this variant was evaluated and shown within the results. This means that instead of 8 strategies, only 7 strategies were evaluated. Table 5.4 shows the resulting measure heights. For every strategy, the height of the first measure is determined. In case of an adaptive strategy, the height of the second measure is determined as well. For every adaptive strategy, two heights for the second measure are given. Either for a situation in which SSP2-4.5 appears to be happening, and a height in case SSP5-8.5 is occurring.

So for example for 'Strategy 3: Adaptive Levee SSP2-4.5', for the initial step a height of 1.48m was found. Then, in case this assumption of SLR was correct: being SSP2-4.5, the next measure is 0.63m. In case the SLR, turns out to be faster and follows the SSP5-8.5 scenario, the height for the second measure is 1.06m.

In Figure 5.5, the steps of determining the measure heights for Strategy 1-4 and Strategy 7 are shown. Heights for Strategy 5 and 6 are left out, as these are the same as Strategy 3 and 4. The blue vertical lines show the relevant timeframes, the horizontal red line is the minimum required safety level. The decreasing graphs represent the decreasing safety level overtime, which is driven by SLR.

Table 5.4: Table with heights of the measures that were used in for the MC-analysis

		Heights [m]		
	Strategy	**1st step**	**2nd step: SSP2-4.5**	**2nd step: SSP5-8.5**
1	Static SSP2-4.5	2.11	n.a	0.43
2	Static SSP5-8.5	2.52	n.a	n.a
3	Adaptive Strategy SSP2-4.5	1.48	0.63	1.06
4	Adaptive Strategy SSP5-8.5	1.56	0.56	0.99
5	Adaptive Strategy with flex. SSP2-4.5	1.48	0.63	1.06
6	Adaptive Strategy with flex. SSP5-8.5	1.56	0.56	0.99
7	Dry flood proofing & Levee SSP2-4.5	1.5	1.82	2.2

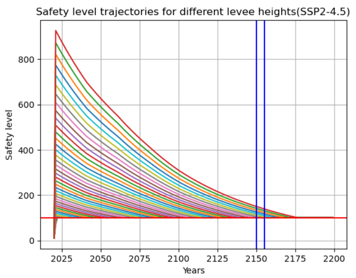
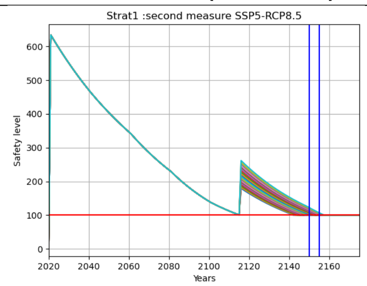
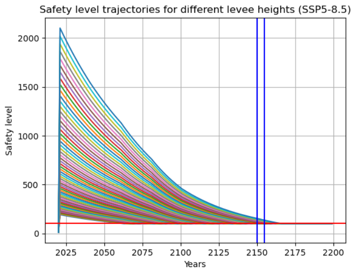
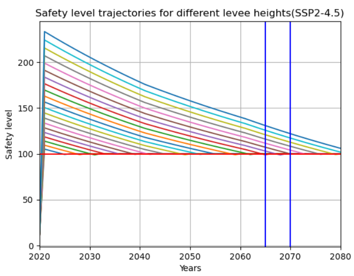
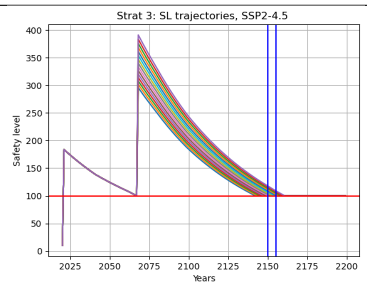
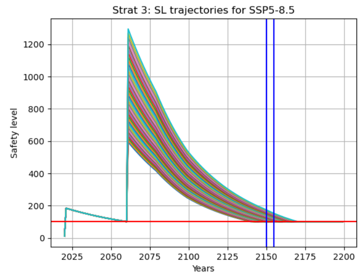
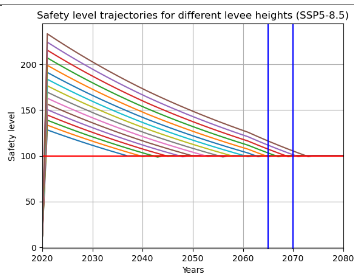
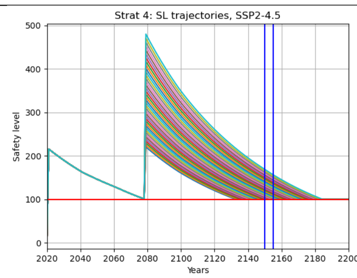
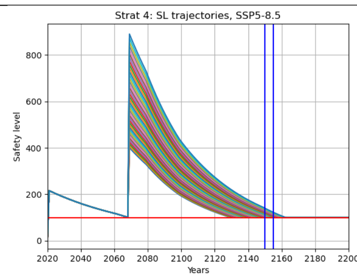
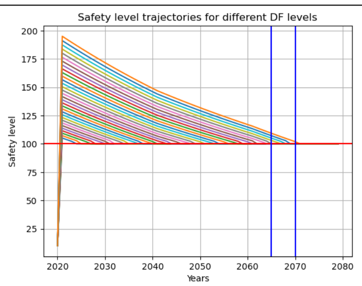
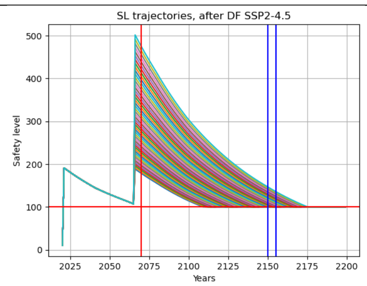
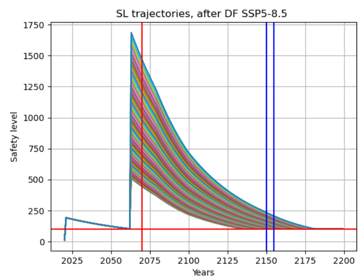
<table>
<tr><th>Strat.</th><th>1st Measure</th><th>2nd Measure (SSP2-4.5)</th><th>2nd Measure (SSP5-8.5)</th></tr>
<tr><td>1</td><td></td><td>n.a</td><td></td></tr>
<tr><td>2</td><td></td><td>n.a</td><td>n.a</td></tr>
<tr><td>3/5</td><td></td><td></td><td></td></tr>
<tr><td>4/6</td><td></td><td></td><td></td></tr>
<tr><td>7</td><td></td><td></td><td></td></tr>
</table>

Table 5.5: Overview of determination of optimal height of the measures. The results are given for all strategies (1-7), the same heights for Strategy 3 and 5, and for Strategy 4 and 6 are used, so they are combined.

5.3.1. Results for deterministic future

From the analysis of the existing evaluation methods, it was found that it is important to evaluate the performance of the strategies for all possible futures. Or, in other words, acknowledge the uncertainties within the variables. Before the strategies were evaluated using a MC-analysis, the performance of the strategies was determined for a deterministic future. In a deterministic future, it is assumed that all variables are known. In the model evaluation, the mean values of the distributions are used. Additionally, no cost-uncertainty factor is included. The results are shown in Table 5.6. The strategies are tested for both SLR-scenarios. So, for example Strategy 3 which starts off assuming a SSP2-4.5 scenario, is tested for a scenario in which this scenario appears to be occurring and for the scenario the SLR-scenario appears to be SSP5-8.5. In this case, the height of the second measure is determined with no uncertainty, which is as discussed earlier unrealistic. However, this analysis provides a good first insight in the economic performance of the strategies. The metrics EAC, PoL and CV are left out as they are not relevant as there is no variance and the results all have the same project horizon.

Table 5.6: Results of the strategy in a deterministic future. The Adaptive strategies are tested for both SLR-scenarios. *For a do-nothing scenario, the NPV describes the value at risk.

	Strategy	SLR- Scenario	NPV* [M€]	BCR [-]	Red. Risk [M€]	Tot. Investment Costs [M€]
0	**Do-Nothing**	SSP2-4.5	-15.63	n.a	0	0
		SSP5-8.5	-17.75	n.a	0	0
1	**Static SSP2-4.5**	SSP2-4.5	8.64	2.37	14.9	6.3
		SSP5-8.5	10.6	2.64	17.1	6.5
2	**Static SSP5-8.5**	SSP2-4.5	8.83	2.15	16.1	7.3
		SSP5-8.5	10.14	2.34	17.5	7.3
3	**Adaptive SSP2-4.5**	SSP2-4.5	9.61	2.76	15.1	5.5
		SSP5-8.5	8.41	2.07	17.3	8.8
4	**Adaptive SSP5-8.5**	SSP2-4.5	9.65	2.78	15.1	5.4
		SSP5-8.5	11.12	2.81	17.3	6.1
5	**Adaptive with flex. SSP2-4.5**	SSP2-4.5	8.74	2.38	15.1	6.34
		SSP5-8.5	10.36	2.49	17.3	6.94
6	**Adaptive with flex. SSP5-8.5**	SSP2-4.5	8.66	2.35	15.1	6.34
		SSP5-8.5	10.31	2.49	17.3	6.94
7	**Dry floodproofing & Levee**	SSP2-4.5	**11.78**	4.60	15.04	3.3
		SSP5-8.5	**13.3**	4.27	17.1	4.01

The outcomes that stand out are listed below.

- The value at risk is higher for a SSP-5-8.5 scenario than in the case of a lower SSP2-4.5 scenario. This is understandable, as higher water levels result in higher inundation levels, which eventually results in higher damages.
- Strategy 7 performs best, no matter the SLR-scenario.
- The performance of the other strategies all very similar. In case Strategy 7 would not be available, the decision between the strategies is less evident. In case one assumes a SSP2-4.5 scenario, Strategy 5 would be the best option with a BCR of 2.38. In case of a SSP5-8.5, Strategy 4 would be the best with a BCR of 2.81.
- As discussed in Chapter 3, this scenario thinking, leaves the decision-maker with the yet important decision, namely which scenario to assume.

5.4. Section D: Economic Performance Evaluation

Before the MC-analysis can be performed, the uncertainties that are included were formulated. For this conceptual case study, four uncertainties are incorporated: the SLR, the inflation rate. the socio-economic growth rate and a cost-uncertainty factor. The uncertainties, the type of distribution and their parameters are listed in Table 5.7.

Table 5.7: Included uncertainties in the Monte Carlo Analysis

Uncertainty Variable	Distribution	Parameters
Inflation Rate	Normal	μ = 0.02, σ= 0.004
Growth Rate	Normal	μ=0.01, σ=0.004
SLR-Scenario	Uniform	n=2, p=0.5
Cost Uncertainty	Log-normal	μ=1, σ=0.001
SLR-rate SSP2-4.5	Normal	μ=1, σ=0.38
SLR-rate SSP5-8.5	Normal	μ=1, σ=0.38
Boundaries SLR-scenario	n.a	5^{th} & 95^{th} quantile

5.4.1. Results

In this section, the results of the strategies are presented. The results are summarized in Table 5.8. The 7 different strategies are listed in the first column, then the economic performance parameters are stated in the top row for all the individual strategies. As discussed above, only a single variant of the Dry flood proofing & Levee combination was evaluated. In Figure 5.9 and Figure 5.10, the results are visualized in plots. The first column shows the SL trajectories, the second and third column show the histograms of the NPV and BCR in which the mean of the results are illustrated with a red dashed line. Additionally, in the histogram of the BCR, a vertical axis is placed at the value '1'. This is the boundary for a profitable strategy (BCR > 1). Finally, the cumulative distributions functions of the NPVs are plotted for the 7 strategies in Figure 5.9. This gives a clear visualization of the PoL metric.

Table 5.8: Results of Conceptual Case Study

	Strategy	NPV Mean [M€]	CV NPV [%]	BCR Mean [-]	CV BCR [%]	EAC Mean [M€]	CV EAC [%]	PoL [%]	Reduced Risk [M€]	Tot. Investm. Costs [M€]
0	Do nothing	-17.32	-9	n.a	n.a	n.a	n.a	n.a	0	0
1	Static SSP2-4.5	10.00	43	2.55	25	0.40	43	0.01	16.41	6.41
2	Static SSP5-8.5	9.66	45	2.32	26	0.39	45	0.01	16.99	7.33
3	Adaptive SSP2-4.5	10.37	39	2.72	21	0.42	39	0.00	16.36	5.99
4	Adaptive SSP5-8.5	10.60	40	2.78	23	0.43	41	0.00	16.48	5.89
5	Adaptive with flex. SSP2-4.5	9.77	45	2.43	24	0.39	45	0.00	16.51	6.74
6	Adaptive with flex. SSP5-8.5	9.72	45	2.42	24	0.39	45	0.00	16.48	6.76
7	Adaptive Levee &DF	12.85	35	4.78	27	0.52	35	0.00	16.41	3.56

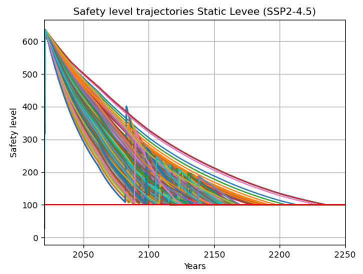
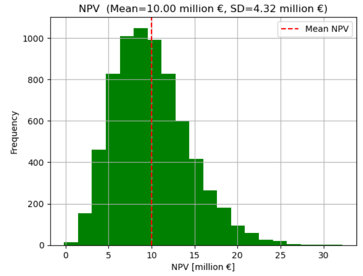
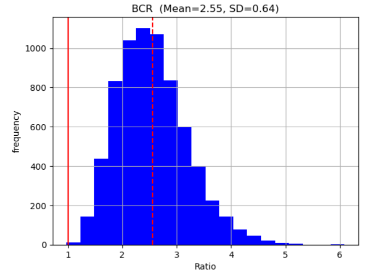
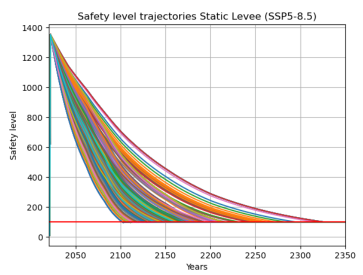
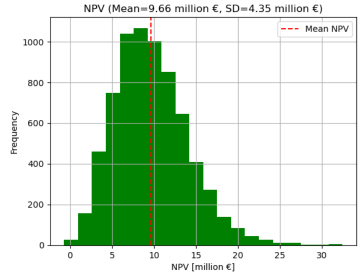
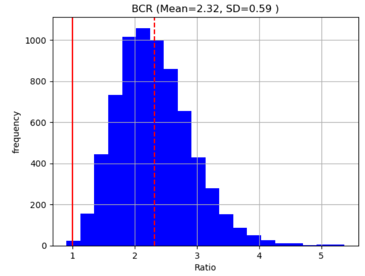
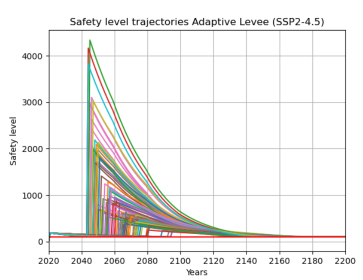
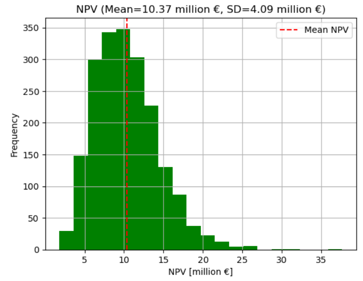
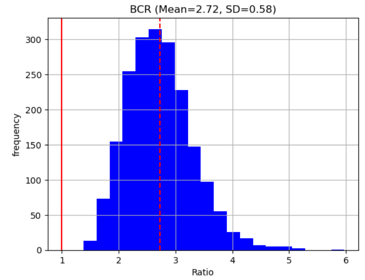
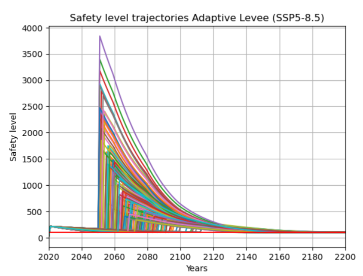
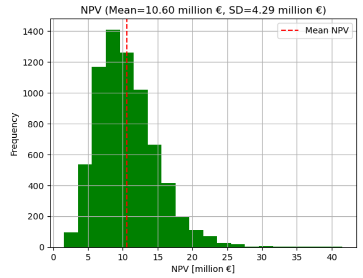
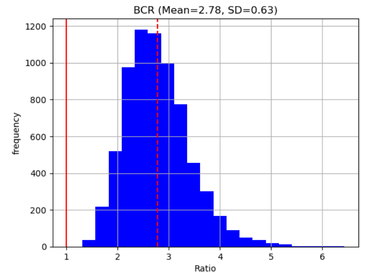
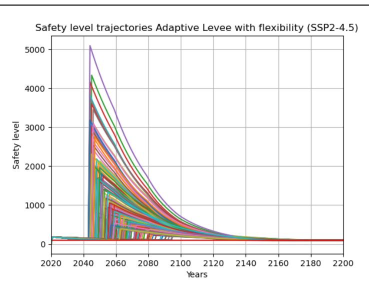
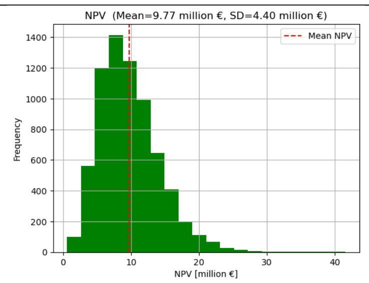
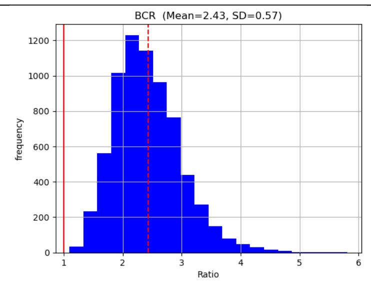
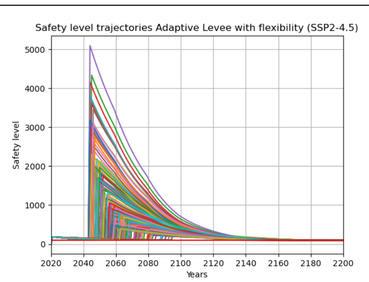
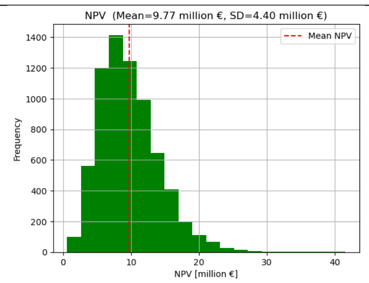
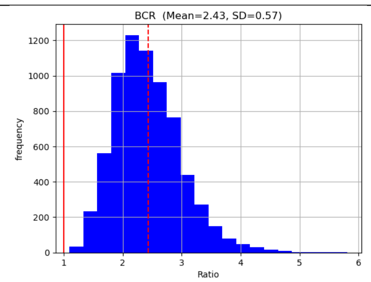
Strat.	SL-Trajectory	NPV	BCR
1			
2			
3			
4			
5			
6			

Table 5.9: Results of Conceptual Case Study (1/2) (plots)

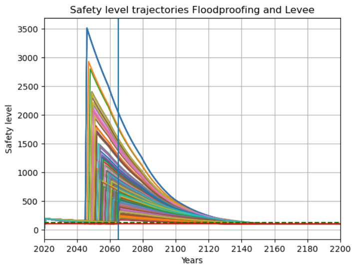
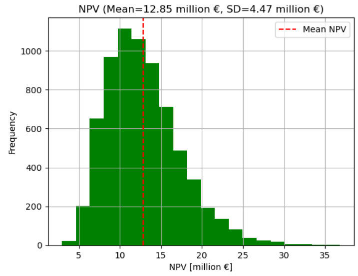
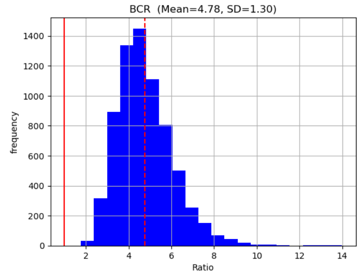
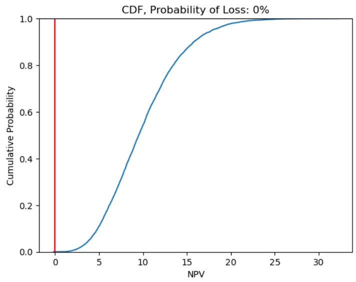
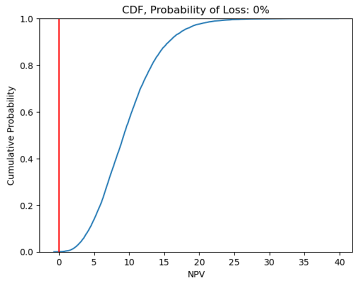
Strat.	SL-Trajectory	NPV	BCR
7			

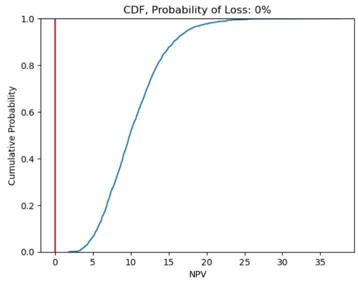
Table 5.10: Results of Conceptual Case Study plots (2/2)



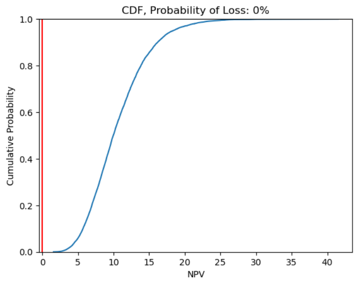
(a) CDF Strategy 1



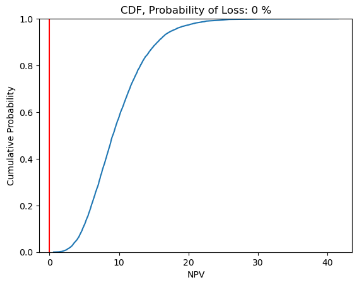
(b) CDF Strategy 2



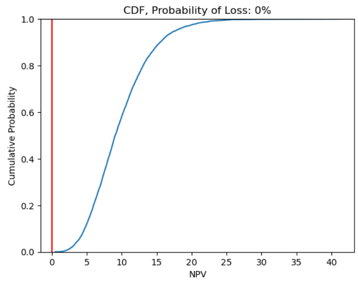
(c) CDF Strategy 3



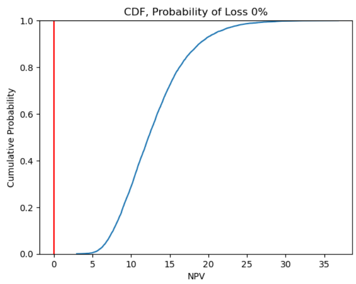
(d) CDF Strategy 4



(e) CDF Strategy 5



(f) CDF Strategy 6



(g) CDF Strategy 7

Figure 5.9: Cumulative Distribution plots for the NPV for all strategies. The red line marks the 0M€ boundary. If the graph is visible on the left side of this boundary, it means that negative values are found.

5.4.2. Analysis of Results

The above presented results give insight in the economic performance of the different strategies.

1. Strategy 0, also referred to as the do-nothing scenario, shows that the average value at risk for a timeframe from 2020 till 2150 is about 17M€. This confirms the assumption that investing in flood risk reduction measures is a good investment opportunity. Of course, this was already necessary as the actual safety level is below the minimal required safety level.
2. The first outcome that stands out is the PoL for all strategies is 0, which indicates that all strategies only show positive outcomes (NPV > 0).
3. For the static approach, Strategy 1 which starts off with an initial SLR scenario being SS2-4.5, shows the better result of the two. The plot of the SL for Strategy 2 in Figure 5.9 shows that a big part of the simulations surpasses the project horizon at 2150. This means that the simulations reach the minimum required lifetime, and therefore the end of the measure's lifetime, after 2150. For these unequal project horizons, the EAC metric was introduced. The EAC and the BCR of Strategy 1 also shows a higher value than for Strategy 2.
4. The next remark about the two static results concerns the total amount of reduced risk (benefits) and the Total Investment Costs. The amount of reduced risk is a bit higher for Strategy 2, which can be explained by the higher SL. However, despite the situation that and extra levee has to be constructed, the total investment costs are lower for Strategy 1. This can be explained by the discounting of the second investment.
5. The reduced risk for Strategy 2 is higher than for a do-nothing scenario, which seems unlogical. However, this outcome can be explained by the fact that in many situations the project horizon for Strategy 2 is longer than 2150, for which the do-nothing scenario was evaluated. This can be seen in Figure 5.9, on the second row. When the project horizon is longer, more risk can be reduced.
6. The first set of adaptive strategies; Strategy 3 and 4, show a slightly higher NPV when initially a SSP5-8.5 strategy was assumed: 10.36M€ vs 10.60M€.
7. Strategy 5 & 6, for which a flexibility premium is paid, the NPV is a little lower. This is caused by the higher total investment costs. It shows that it is economic more efficient to postpone the extra costs than paying extra in advance.
8. For the strategy in which dry flood proofing was combined with a levee has only one variant as explained above. The NPV and EAC is the highest of all the strategies. Remarkable is that the amount of risk is comparable to the other strategies. The low investment costs lead to the high performance of the strategy. The total investment costs for this strategy are the lowest of all the strategies, by almost 40%.
9. When evaluating the histograms of the NPV and the BCR in Figure 5.9, it's clear that the spread is comparable to all the strategies. The CV shows equal results to for all the Strategies.
10. The final remark concerns the amount of reduced risk. Despite the fact that, to the eye, the SL-trajectories vary between the strategies, especially the static vs the adaptive. The results show, that despite the lower SL at the start of the strategy, the amount of reduced risk does not differ a lot.

5.4.3. Stochastic future vs Deterministic future

At this point, the strategies are evaluated for a deterministic and stochastic future, in which uncertainty is incorporated. Below, the most important differences between these outcomes are listed.

- The first point that stands out is that Strategy 7 is the best strategy for both situations. This is in line with the first finding that despite which SLR-would occur, Strategy 7 was already the best choice.

- In the deterministic evaluation, the second best performing strategies were either strategy 4 for the SSP2-4.5 scenario and Strategy 5 for the SSP5-8.5 scenario. When uncertainties are included, Strategy 4 is clearly better performing than Strategy 5 with a BCR of 2.78 versus a BCR of 2.43.
- Remarkable to see is that in case the strategies were tested for the two SLR-scenarios at the same time, the results are higher than the averaged outcomes for the SSP2-4.5 and SSP5.8.5 scenerio.

5.4.4. Uncertainty Analysis

The above results were generated by means of a MC-analysis. This technique generates a set of scenarios by sampling from the defined probability distributions, which then results in an estimated range of possible outcomes. However, the MC-analysis doesn't provide an exhaustive picture of the model's reliability, as the level of uncertainty connected to each outcome is not considered. For this reason, an uncertainty analysis is performed, as this enables quantifying the level of uncertainty associated with each stochastic input parameter. Multiple technique exists to perform an uncertainty analysis, ranging from more basic (e.g. the Morris-method), to more advanced multidimensional analyses (e.g. Sobol/Saltelli's indices) (Wainwright, Finsterle, Jung, Zhou, & Birkholzer, 2014). For this research, the Morris-method (also known as a one-at-a-time approach (OAT)), has been used. The analysis has been performed for the three different kind of strategies that were tested; the static strategy, the adaptive strategy with only a levee as the included measure, and the adaptive strategy in which dry proofing and a levee were combined. For every type of strategy, the CV has been determined. Next, the CV was determined, but then keeping one of the variables deterministic. This method, enables to indicate how the CV changes when a variable is included as a deterministic value, and therefore shows its influence on the total variance. The limitation of this first-order method is that it only shows the individual contribution to the variance. A total order analysis, includes the interaction between the variables, and how this would impact the total output variance. However, for this analysis, the Morris method was used, for computational reasons.

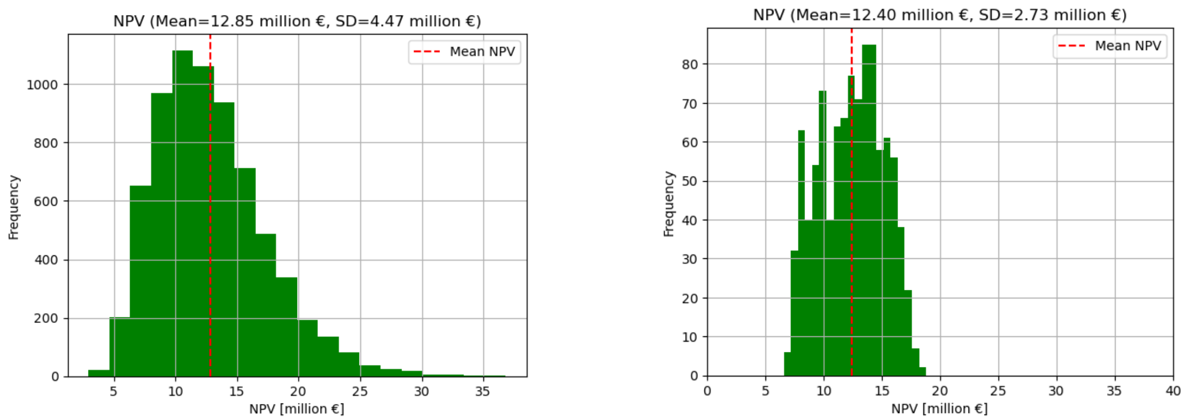
In Table 5.11, the results of the uncertainty analysis are presented. Only one for every type of variant is shown, as the results were almost the same. Furthermore, only the NPV metric is evaluated. First, the CVs for the strategies were determined again, as due to computational power less simulations than that were used for the MC-analysis could be performed. The analysis of the results of the uncertainty analysis are listed below.

- For the static strategies, the uncertainty of the SLR-rate and the economic growth rate have the greatest influence. The CV is about 25% lower when these variables are deterministic. The fact that these three turn out to be important indicate that the amount of risk is relevant to the performance of the strategy. All three variables are directly related to the amount of risk.
- For the adaptive strategies with only levees, it stands out that all the variables contribute a lot to the uncertainty of the outcome. Indicating that the variance of the outcome is created by the combination of all the uncertainty variables. Although all variables are influential, the economic growth shows the biggest influence, the CV is halved, from 49% to 22% when this variable is deterministic.
- The CV of the NPV of the adaptive strategy which starts with dry flood proofing is hardly influenced by the SLR-scenario or the SLR-rate. The economic growth shows to be the most influential. The CV reduced from 29% to only 5% which is a reduction of about 80%.

To validate point three of the above findings, the growth factor has been set deterministic for Strategy 7. These results of the MC-analyis are shown in Figure 5.10. In Figure 5.10a, the original histogram of the NPV for Strategy 7 is shown, in Figure 5.10b the results of the NPV histogram is depicted. The reduction of the uncertainty is clearly visible by the spread of the histogram, the SD has indeed changed from 4.47M€ to 2.73M€.

Table 5.11: Results of uncertainty analysis for the 3 different type of strategies performed on the NPV metric. *The number of buildings was included for the strategy that included dry proofing as measure. For the other strategies, the no. of buildings is not relevant

	Static	**Adaptive - levee**	**Adaptive - DF**
Variable	*CV NPV [%]*	*CV NPV [%]*	*CV NPV [%]*
All Stochastic	42	49	29
Individual variable set to deterministic:			
SLR - scenario	49	39	29
SLR- rate	37	30	27
Cost Uncertainty	44	40	30
Inflation rate	41	36	26
Economic -growth rate	30	22	5
*No of buildings**			29



(a) NPV (original)

(b) NPV with deterministic growth rate

Figure 5.10: NPV and CV plots for Strategy 7, in which the growth rate is changed to a deterministic variable. The outcome validates the finding from the uncertainty test.

5.5. Sensitivity Analysis

Considering the found results and the results from the uncertainty analysis, four sensitivity tests were formulated. The first three sensitivity tests are based on earlier mentioned influential factors on a flood risk reduction strategy, discussed in Chapter 3. The other sensitivity test are direct results of the outcome of the uncertainty analysis. Below, the reasoning behind the choice of the sensitivity test are formulated. Next, the result of the sensitivity test are presented in table form. To enhance the comparison between the original case study and the sensitivity test, an extra column was added to the table. The second column of the results shows the change in NPV with respect to the outcome of the original case study. The plots of all the results can be found in Appendix B. The CDF plots are only included if the variants show PoL greater than 0 and therefore provide useful information.

1. At this point, the minimal required safety level was assumed to be 1:100 years and was not based on any calculation or reasoning. The minimal required safety is important for determining the cost optimal measures, and therefore impacts the amount of reduced risk and the investment costs. To investigate the impact of the assumption, the minimal required safety level was increased to 1:1000 per year.

2. In the framework, extra knowledge about the experienced SLR is used to define the measure height of the second investment. This was identified as one of the strengths of adaptive planning. To investigate this potential gain, the second sensitivity test focussed on the influence of this knowledge. To test this, the heights of the second measure are based on the initial determined heights for either the SSP2-4.5 or the SSP5-8.5 scenario.

3. In the analysis, the SSP2-4.5 and SSP5-8-5 are considered to have an equal probability to occur. As the uncertainty analysis showed, the SLR-scenario has impact on the variance of the results. Therefore, a sensitivity analysis was performed on this assumed probability. The probability of the SSP2-4.5 scenario is reduced from 50% to 25%, which seems more logical than the other way around, based on the last synthesis report of the IPCC (Boehm & Schumer, n.d.). In this report, one of the messages was that immediate action is required, if the 1.5 and even the 2 degrees threshold of global heating wants to be met.

4. The uncertainty test showed that the economic growth factor was influential to the uncertainty of the outcomes. The economic growth is used to quantify the amount of risk. To further investigate this impact, the economic growth factor was doubled.

5.5.1. Sensitivity Test 1: Minimal Required Safety Level

For this sensitivity test, the minimal required safety level was increased from 1:100 per year to 1:1000 per year. Strategy 7 that started with dry floodproofing is no longer included in the results. The step from 1:10 per year to 1:1000 per year required a height of dry flood proofing greater than the maximum height of 1.5m. The most remarkable findings are listed below.

Table 5.12: Results of Sensitivity Test: The minimal required safety level

	Strategy	NPV Mean [M€]	w.r.t Org. [+-%]	CV NPV [%]	BCR Mean [-]	CV BCR [%]	EAC Mean [M€]	CV EAC [%]	PoL [%]	Reduced Risk [M€]	Tot. Investm. Costs [M€]
0	Do nothing	-17.3	0	-9	n.a	n.a	n.a	n.a	n.a	0	0
1	Static SSP2-4.5	7.49	-25	58	1.78	25	0.30	58	1.40	17.04	9.55
2	Static SSP5-8.5	6.84	-29	63	1.66	25	0.28	64	3.37	17.20	10.36
3	Adaptive SSP2-4.5	7.72	-25	53	1.83	22	0.31	53	0.10	16.81	9.11
4	Adaptive SSP5-8.5	8.08	-23	54	1.88	23	0.33	54	0.26	17.12	9.06
5	Adaptive with flex. SSP2-4.5	6.44	-34	69	1.59	24	0.26	69	3.36	17.10	10.67
6	Adaptive with flex. SSP5-8.5	6.44	-33	69	1.59	25	0.26	69	3.63	17.12	10.69

- The expected damage in case of a 'do- nothing scenario' did not change, which is logical, as the minimal required safety level does not impact the value at risk.
- The NPV for all strategies reduced, ranging from 22% to 34%.
- The amount of reduced risk [M€] increased for all the strategies, which can be explained by the higher protection level. However, the extra amount of risk is on average only 3%. On the other hand, the total investment costs have increased more, on average the costs increased with about 50%.
- The results show that increasing the minimal required safety level results in less economic efficient strategies. Despite the higher investments, the benefits are marginally increased, which is clearly visible considering the BCRs. On average, they have decreased with 30%. Additionally, PoLs greater than 0 were found which can be seen when analysing the CDF plot of the NPV. In Figure 5.11, the CDF of Strategy 7 is provided.
- The adaptive strategies, that include the flexibility premium, show a higher reduction in NPV than for the strategies without the premium. The higher upfront costs to reach the higher SL, weigh higher than the benefits later in time.

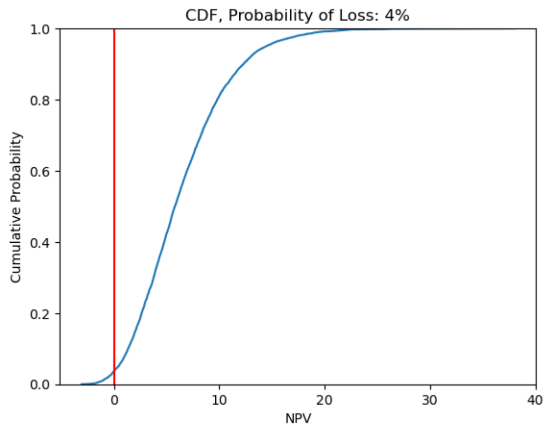


Figure 5.11: Plot of the CDF of Strategy 7 for the sensitivity test in which the minimal required safety level was increased from 1:100 per year to 1:1000 per year

5.5.2. Sensitivity Test 2: SLR - knowledge

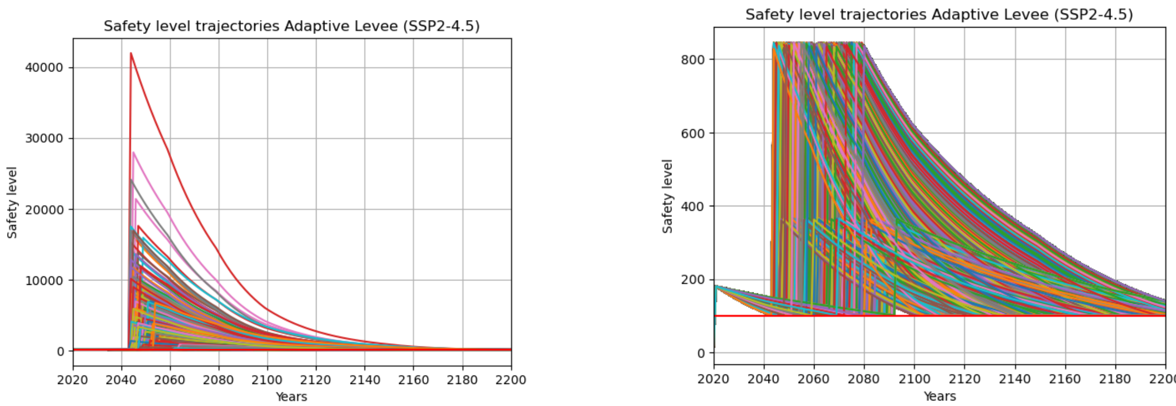
Before the MC-analysis was performed, the heights for the different strategies for different SLR-scenarios were derived. These heights were listed in Table 5.4. To evaluate the value of flexibility, being able to adjust the heights based on experienced SLR, the heights are not altered. So in case SSP2-4.5 scenario is experienced, the height for this scenario is used, no matter the rate that is experienced within this scenario.

Table 5.13: Results of Sensitivity Test 2: SLR-Knowledge

	Strategy	NPV Mean [M€]	w.r.t Org. [+-%]	CV NPV [%]	BCR Mean [-]	CV BCR [%]	EAC Mean [M€]	CV EAC [%]	PoL [%]	Reduced Risk [M€]	Tot. Investm. Costs [M€]
0	Do nothing	-17.3	0	-9	n.a	n.a	n.a	n.a	n.a	0	0
1	Static SSP2-4.5	9.98	0	43	2.55	25	0.40	43	0	16.38	6.40
2	Static SSP5-8.5	9.66	0	45	2.32	26	0.39	45	0	16.99	7.33
3	Adaptive SSP2-4.5	9.90	-5	37	2.69	22	0.41	38	0	16.23	6.03
4	Adaptive SSP5-8.5	10.03	-5	37	2.75	22	0.42	38	0	16.23	5.89
5	Adaptive with flex. SSP2-4.5	9.21	-6	41	2.40	23	0.38	41	0	16.23	6.74
6	Adaptive with flex. SSP5-8.5	9.18	-6	41	2.39	23	0.38	42	0	17.51	6.40
7	DF& Levee	12.00	-7	31	4.36	28	0.50	32	0	16.20	3.83

The most remarkable findings are listed below.

- As expected, the value at risk did not change. Additionally, the results of the static Strategy 1 and 2, did not change as well because for these strategies, no SLR-knowledge is incorporated.
- The option to adjust the height based on the new available data shows to be valuable for the adaptive strategies.The performance of all strategies decreased w.r.t the original situation. The performance decreased with 5% to 7%.
- When looking at the SL-trajectories for strategies 3-6, it stands out that the project horizon is much longer. In Figure 5.12 the trajectory is shown for Strategy 3. This difference in lifetime emphasizes the evaluation of the EAC, next to the NPV. Furthermore, the figures show that the SL is on average a bit lower, this can explain the lower amount of reduced risk.



(a) SL-Trajectory Strat 3 (original)

(b) SL-Trajectory Strat 3 (Sensitivity Test)

Figure 5.12: SL-Trajectories for Strategy 3 for the original situation and the sensitivity test. For the sensitivity test, the spread in project horizon is much bigger

5.5.3. Results of Sensitivity Test 3: SLR-scenario

The probability for the SLR-scenario has been adjusted. Initially, the chance for either scenario to occur was 50/50. The chances shifted to a 25% chance for scenario SSP2-4.5 and 75% chance for SSP5-8.5.

Table 5.14: Results of Sensitivity Test, SLR-scenario

	Strategy	NPV Mean [M€]	w.r.t Org. [+-%]	CV NPV [%]	BCR Mean [-]	CV BCR [%]	EAC Mean [M€]	CV EAC [%]	PoL [%]	Reduced Risk [M€]	Tot. Investm. Costs [M€]
0	Do nothing	-17.18	3	-9	n.a	n.a	n.a	n.a	n.a	0	0
1	Static SSP2-4.5	10.32	3	43	2.58	25.06	0.42	43	0	16.78	6.46
2	Static SSP5-8.5	9.90	3	43	2.35	24.60	0.40	43	0	17.23	7.33
3	Adaptive SSP2-4.5	10.70	3	39	2.72	21.42	0.43	39	0	16.89	6.19
4	Adaptive SSP5-8.5	10.98	4	41	2.79	22.72	0.44	41	0	17.07	6.08
5	Adaptive with flex. SSP2-4.5	10.17	4	45	2.45	23.51	0.41	45	0	17.07	6.90
6	Adaptive with flex. SSP5-8.5	10.16	5	45	2.45	24.04	0.41	45	0	17.07	6.91
7	DF& Levee	13.19	3	35	4.68	26.88	0.53	34	0	16.93	3.75

The most remarkable findings are listed below.

- The value at risk increases with only 3%, from 16.7M€ to 17.18M€. The amount of reduced risk has increased for every strategy.
- This increase of 3% in value at risk is directly translated to the increase of the performance of the metrics. The increase ranges from 3-5%.

5.5.4. Sensitivity Test 4 - Growth rate

As discussed earlier, a sensitivity test was performed in order to investigate the impact of the growth rate. For all the different strategies, the uncertainty test showed that the growth rate contributed to the uncertainty of the outcome.

- By increasing the annual growth rate from 1% to 2% showed to have a significant impact on the absolute outcomes of the results. Most NPVs more than doubled. As the growth factor only impacts the reduced risk, and not the investment costs, the BCR of the strategies even quadrupled.
- When considering the relative change of the strategies, the impact is less significant. Strategy 7 remains the best performing strategy.
- For the original case study, the second-best strategy were Strategy 3 and 4. In this situation, Strategy 2 increased most and results in second best performing strategy. This increased performance can be explained by the higher amount of reduced risk, the higher SL in Strategy 2 has now more added value.

Table 5.15: Results of Sensitivity Test 4: Growth-rate

	Strategy	NPV Mean [M€]	w.r.t Org. [+-%]	CV NPV [%]	BCR Mean [-]	CV BCR [%]	EAC Mean [M€]	CV EAC [%]	PoL [%]	Reduced Risk [M€]	Tot. Investm. Costs [M€]
0	Do nothing	-28.51	70	-9	n.a	n.a	n.a	n.a	n.a	0	0
1	Static SSP2-4.5	22.19	122	36	4.45	27	0.89	37	0.00	28.60	6.41
2	Static SSP5-8.5	23.19	140	39	4.16	29	0.93	39	0.00	30.52	7.33
3	Adaptive SSP2-4.5	22.54	117	38	4.73	26	0.91	38	0.00	28.54	6.00
4	Adaptive SSP5-8.5	23.11	118	39	4.88	27	0.93	39	0.00	29.02	5.91
5	Adaptive with flex. SSP2-4.5	22.16	127	41	4.25	28	0.89	41	0.00	28.91	6.75
6	Adaptive with flex. SSP5-8.5	22.24	129	41	4.25	28	0.90	41	0.00	29.02	6.78
7	DF& Levee	25.29	97	38	8.22	31	1.02	38	0.00	28.92	3.64

6 Discussion

This chapter contains a discussion on the methods and results of the research and the associated implications for the main conclusions. The points of discussion are subdivided into three sections. In Section 6.1, the outcomes of the case study and the sensitivity tests are discussed. Then in Section 6.2, the discussion points that relate to the input of the framework are described. Finally, the framework itself and how it could be applied for an actual case study is discussed in Section 6.3.

6.1. Discussion of Results

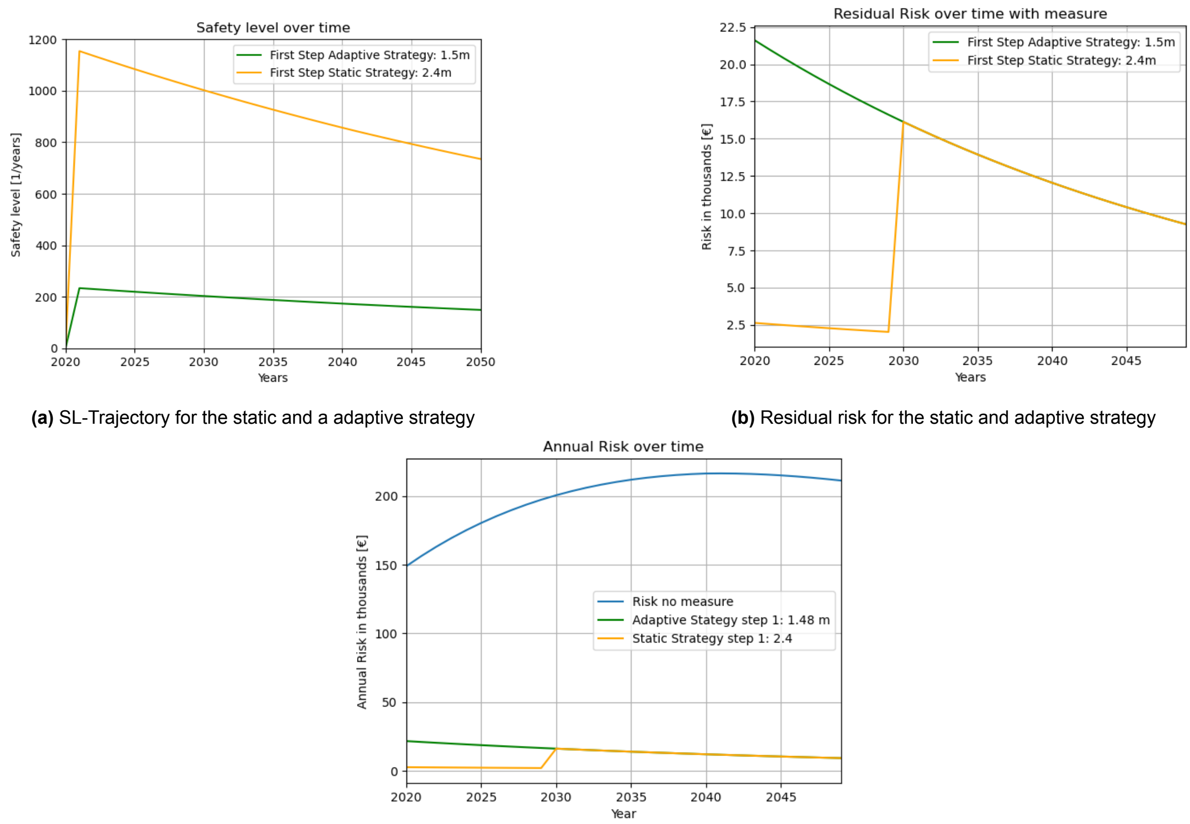
In this section, the results of the conceptual case study and the sensitivity tests are discussed.

6.1.1. Reduced Risk

The first aspect that stands out when evaluating the outcomes of the strategies, is the difference in reduced risk between the adaptive strategies and the static strategies. Despite the lower initial safety level for the adaptive strategies, the difference in the amount of reduced risk is minimal. In Figure 6.1 the impact of the different safety levels and the corresponding reduced risk is shown. For this example, Strategy 2 and Strategy 3 are used and are compared for the time period between 2020 and 2050. In Figure 6.1a, the SL- trajectory of the first years of the static and the adaptive strategy are shown. The static strategy has a higher safety level (measure height: 2.4m) when compared to the adaptive strategy (measure height: 1.4m). In Figure 6.1b, the difference in residual risk is clearly visible. The residual risk for the static strategy starts off around 2.5k€/year, after which it makes a jump just before 2030, to 16k€/year, the same level as the adaptive strategy. This jump can be explained by the fact that at that moment, the SL of the static strategy turns just below 1:1000 per year. This level is used in the calculation of the annual risk, see Equation 4.5. The amount of residual risk, for a safety level of 1:150 per year and 1:990 per year, returns the same result. The residual risk for the evaluated time period is for the adaptive strategy is total 440k€ and for the static strategy only 270k€ (60% lower). However, when this difference of residual risk is compared to the risk in case of no measures, the difference between the two strategies shows to be relatively small. This is clearly visible in Figure 6.1c. The difference in total reduced risk for the adaptive strategy is 5.6M€ and for the static strategy 5.7M€ which is only a difference of 2%. This confirms the results of the minimal difference in reduced risk for the adaptive and the static strategies.

6.1.2. Total Investment Costs

The second factor concerns the difference in the amount of total investment costs for the different strategies. Strategy 7, the variant that started off with dry floodproofing turned out to be the best performing strategy. As the results showed, this was achieved by the relatively low investment costs. For the example discussed above, the first investment for the adaptive strategy (including O&M costs) is 4.2M€ and for the static 6.9M€. The costs for dry floodroofing only resulted in a total costs of 0.2M€. It shows that, when the measures with lower investment costs can achieve the same safety level, these are preferred.



(a) SL-Trajectory for the static and a adaptive strategy

(b) Residual risk for the static and adaptive strategy

(c) Annual Risk over time in present value

Figure 6.1: This figure illustrates the difference of SL and the impact on the amount of reduced risk. The higher SL (a), shows a lower residual risk (b) however when this is compared with the total amount of reduced risk, the impact is relatively small (c)

However, for the situation that the minimal required safety level was higher, dry floodproofing was no longer an option as it surpassed the maximal height. So, the suitability of a measure differs per situation.

6.1.3. Minimal Required Safety level

The third aspect of the results that is discussed concerns the minimal required safety level. The determination was out of scope, and so a certain safety level was assumed. However, this safety level plays an important role in the determination of the measures heights, and subsequently in the gained benefits. Additionally, in the analysis, a new measure was implemented if the minimal required safety level was met. So, an accurate minimal required safety level is important. This influence was confirmed by the sensitivity test in which the minimal required safety level was increased to 1:1000 per year. The BCR of the strategies decreased with about 30%. Additionally, the adaptive strategies with the flexibility premium were affected more than the adaptive strategies without. Furthermore, only this sensitivity test showed negative outcomes and therefore showed PoLs greater than 0. The framework showed to be robust, nevertheless, determining the optimal minimal required safety level is important.

6.1.4. Probability of Sea Level Rise Scenario

For the analysis, two SLR-scenario were included. An equal probability to either one of the scenario's occurring was assumed. The uncertainty analysis showed that the scenario that was sampled, was a variable that contributed to the variance of the results. In the sensitivity test, the impact on the results showed to be minimal (3-6% change). This influence can be explained by evaluating the annual risk over time for both included scenarios. In Figure 6.2 the annual risk overtime is plotted in two manners, as the future value and as the present value. The annual risk for the two different SLR-scenarios are plotted. Due to SLR, the annual risk increases overtime, this is the shown by the higher two plots.

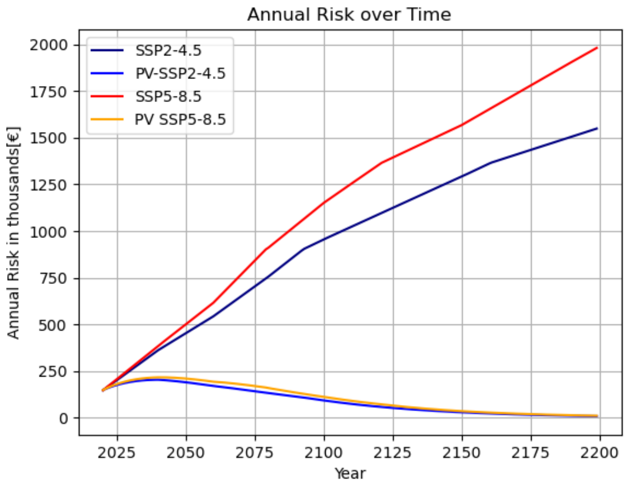


Figure 6.2: In this plot, both the future and the present value of the annual risk are plotted. The plots are shown for the SSP2-4-5 and SSP5-8.5 scenario

However, in a CBA, future cashflows are correct for the economic growth, and discounted to illustrate the present value. The present value of the annual risk first increases for a short amount of time, after which the annual risk decreases rapidly. The difference between the two scenarios are clearly visible when the cashflow is not discounted. But, this clear difference diminishes after a while. The difference of the impact between the SLR-scenario's becomes more evident after 2100, however this has minimal impact on the outcomes due to the discounting.

6.1.5. Flexibility Premium

From the study into ROA, the idea of creating 'options' in or on the system, was inspired. In the formulated strategies, this was fulfilled by including a strategy with a flexibility premium. For all tested cases, the adaptive strategies without the flexibility premium performed better than the variants with the flexibility premium. The sensitivity test showed some differences in the amount of impact in the results, however these differences were relatively small. The adaptive strategies with flexibility premium gained most profit from the higher growth rate and the higher chance on a high SLR scenario. When the chances are higher, that a second 'high' investment will be necessary, the upfront extra costs for the first investment are worth it as it makes the second investment less expensive. For situations in which there is a high probability the future costs for a second investment are much higher, this strategy will become more economically efficient.

6.2. Input & Output of framework

In this the section, the discussion points related to the input and output data of the framework are discussed.

6.2.1. Costs

In order to evaluate the economic performance of the different reduction strategies, the costs of the different measures are defined. The discussion about this topic consist of two parts.

The first topic concerns the costs of measures. For this research, literature about raising existing levees dating from 2013 has been used. However, for in case of adaptive strategies, the same values (corrected by inflation) are used. However, with all the technological advancement and new ways of building is it reasonable to assume that innovations can result is reduction of costs. Salehi and Burgueño (2018) reviewed recent developments in the application of artificial intelligence (AI) methods in the field of structural engineering. The findings suggest that AI methods have the ability to significantly improve the cost-efficiency in structural engineering through improvements in maintenance planning, generation of cost-effective designs and reduction in time-consuming inspections. Furthermore, new materials for measures are being tested.

For example, Ko and Kang (2020) showed how biopolymer reinforcement can the tensile strength and shear resistance of the levee material, leading to improved resistance to erosion and breach development. Which subsequently leads to cost reductions. These are just 2 recent examples of literature showing the potential of cost-reductions. It can therefore be argued that assuming no cost reductions in a timespan 70 years (average time until the second measure was implemented in the case study), is a conservative approach, which is not in favour of adaptive strategies.

The second aspect concerns a cost category which is not included in the framework. In this research, only costs directly connected to the construction of the measure are included. However, it can be argued whether these are the only costs of a flood risk reduction strategy. For example, Don and Stolwijk (2003) listed 'Loss of environmental quality', as a cost category for one of the Deltaworks. Approaches for (monetary) evaluation of this category exist, but they are not standardized or undisputed and were therefore left out of the framework. However, with an increasing focus on the environmental friendly and sustainable solutions, which are partly driven by regulations, it can be justified that the environmental impact should be quantified and included. Quantifying these costs would influence the choice between different measures, will put extra pressure on the 'optimal' design and also on the type of strategy. When environmental costs for are included, over dimensioning, which is a risk in a static approach, will become more expensive. On the other hand, building twice in an adaptive strategy, will result in extra environmental costs as well. Finally, for all measures, constant monitoring is required, especially near the projected end lifetime of the measure. However, in case of short term measures, this monitoring is already much more important after the measure is built. These early costs in case of adaptive, short term strategies, weigh relatively more in the early years due to the discounting, then when performed later. Therefore, it can be argued that the adaptive strategies are a little favoured over the static strategies with the used method as no monitoring cost are included.

6.2.2. Damages

As described in Section 4.1, only direct physical damages were included as consequences of a flood event. Indirect losses or loss of life were not included. Therefore, the calculated benefits were not exhaustive. However, as it still concerned a conceptual case study, this could be justified. The shape of the project area and therefore the ratio of 'magnitude/length of measures' to protection area is hypothetical. In practice, the area could be double the size for example with the same stretch open to the coast. The point of this example is that excluding the above-mentioned benefits will not have jeopardized the accuracy of the conceptual case study, as this was already hypothetical. The framework is able to include different damage cost categories and is not a limitation. As mentioned earlier, the focus of this study was not the exactness of the outcomes, but being able to quantify the response of the performance at a higher level. To show the susceptibility to different input variables, the conceptual case study was tested for an industrial area. In Figure 6.3, the damage curve of the industrial land use type and the residential land use type is depicted. In Table 6.1 the impact on the results when a damage curve for an industrial land use is applied are shown. Additionally, the relative performance between the averaged static variants and the averaged adaptive variants is calculated. The results show that the adaptive strategies are performing much better, as the ratio between the residual risk and the investment costs is relatively more important when the risk in case of no measures is lower. This example both validates the point made in section 6.1.1 about the reduced risk, and the point made in this section about the arbitrarily defined shape/investment/reduced risk ratio.

6.2.3. Metrics of Results

The study into different existing evaluation methods resulted into the incorporation of more metrics next to the commonly used metrics NPV and BCR. The PoL and the CV were added to the evaluation metrics. The PoL showed only to be relevant for one sensitivity test, for the other analyses, the PoL was 0. For this conceptual case study, the added value is arguable. However, the calculation is rather simple and only variables that are already defined are required (number of samples and the NPV for each sample). Therefore, as the extra effort is minimal, the metric can remain included and might show its value for different case study. To propose an alternative metric for the PoL, the metric 'Value at Risk' (VaR) can be considered. The VaR can be used to quantify the potential losses of a strategy. Unlike just considering the PoL, the VaR incorporates both the likelihood and magnitude of potential losses, offering a more comprehensive understanding of risk (Linsmeier & Pearson, 2000).

Table 6.1: Impact damage curve

	Strategy	Original - Residential Land use NPV [M€]	Red. Risk [M€]	Investm. [M€]	Relative Diff.[%]	New - Industrial Land use NPV [M€]	Red. Risk [M€]	Investm. [M€]	Relative Diff. [%]
0	Do nothing	-16.69	n.a	n.a	n.a	-11.07	n.a	n.a	n.a
1	Static SSP2-4.5	10.00	16.41	6.41	Base	4.20	10.53	6.33	Base
2	Static SSP5-8.5	9.66	16.99	7.33		3.86	11.19	7.33	
3	Adaptive SSP2-4.5	10.37	16.36	5.99	+7%	4.75	10.74	5.99	+20%
4	Adaptive SSP5-8.5	10.60	16.48	5.89		4.85	10.73	5.89	
5	Adaptive with flex. SSP2-4.5	9.77	16.51	6.74	-2%	4.00	10.74	6.73	-1%
6	Adaptive with flex. SSP5-8.5	9.72	16.48	6.76		3.97	10.73	6.76	
7	Dry floodproofing & Levee	12.85	16.41	3.56	+31%	7.19	10.77	3.58	+79%

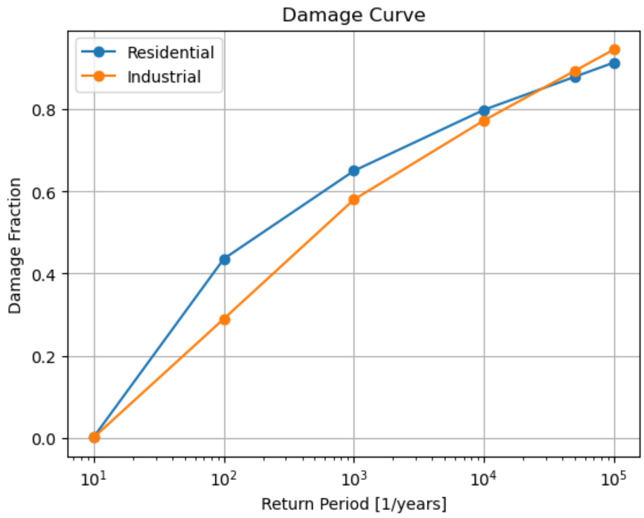


Figure 6.3: Plots of two damage curves for the residential land use type and the industrial land-use type

As an example; a strategy can have 95% VaR of €10,000, meaning there is a 5% chance of experiencing losses exceeding €10,000. This metric is more complex to determine, but gives more insights in the actual loss. The VaR would support the CDF-plot as it tells more about the actual magnitude of the losses than the frequency.

The second metric that was included was the CV. The CV didn't provide additional insights in the evaluation of the strategies. Just like for the PoL, the calculation of the CV is simple and doesn't require much extra effort. So one can decide to include the metric, as it might provide valuable insights for other case studies. Next to the NPV, BCR, PoL and the CV, the amount of reduced risk and the total investment costs were explicitly listed in the presentation of the results. Although these were not considered as a newly introduced features, the insight that it provided were valuable. It gave a better insight on the NPV and BCR.

6.3. Framework: methods used and limitations

This section focussed on the methods and assumptions that were made in framework.The methods that are used are discussed, and finally some limitations are discussed.

6.3.1. SLR- Knowledge

In the framework, a method was developed that enabled adjusting the second investment based on the newly obtained data. For the method, it was assumed that the amount of absolute variance of the SLR projection remained stable overtime.

Recently, in March 2023, the IPCC published the Synthesis Report as the final instalment of the Sixth Assessment Report (AR6), which provides a comprehensive review of the current understanding of the climate. One of the takeaways, was the alarming statement that serious actions should be taken quickly to remain under the 2° degrees, and even better the 1.5 °. With the current formulated plans of the countries within the Paris Agreement, the CO_2 reduction would be reduced with 9% in 2030. However, 43% is needed to remain under the 1.5°. Although this is not stated in the report, one can argue how realistic this target has become. As a consequence, the lower scenarios would become less realistic, and therefore, reducing the spread of the combined scenarios. On the other hand, with the current knowledge, are the 'high' scenario's, still 'high' enough, is a question that can be countered. The framework however offers the opportunity to include more SLR-scenarios than 2, and probabilities can be adjusted accordingly. The coming years can be considered as defining years, and therefore it was assumed that the absolute variance of the SLR will remain the same. As the coming years are seen as decisive, it is a conservative assumption, and might indicate that the SD of the second SLR-factor can be reduced. This means that the newly available knowledge, which becomes available after 30–50 years, will provide more insights about the future than that is currently assumed in this study.

The sensitivity test showed that the performance of the strategies reduced with about 6% when the available knowledge was not used. The most profits were achieved by the reduction in investment costs when lower measures were needed. In monetary terms, it can be argued that the reduction is minimal and the impact of the newly available knowledge is limited. However, this does not mean the feature is not important, in case the amount SLR would also influence the type of measure for example, the impact could turn out to be greater. If less expensive measures could be applied, for example, the impact would be more significant.

6.3.2. Economic Appreciation

This framework is based on the methods of a traditional CBA. An important factor concerns how future cashflows are valued, and therefore which discount factor is used. As discussed in Chapter 3, the discount rate was considered as a political decision, and therefore not included as a stochastic or disputable variable. As a result, no sensitivity test was preformed that focussed on the discount rate. However, it is relevant to discuss as it impacts the preference for static and adaptive strategies.

Choosing an appropriate discount rate for evaluating flood risk reduction strategies entails ethical and political considerations (Beckerman, Hepburn, et al., 2007). Ethically, the discount rate determines the distribution of costs and benefits across time and generations. A higher discount rate may prioritize the present generation, potentially neglecting the welfare of future generations. This can raise concerns about the fairness between different generations. In contrast, a lower discount rate gives more weight to the well-being of future generations, emphasizing the fair distribution of benefits over time and acknowledging the moral responsibility to mitigate their risks. The Stern Review argues that traditional discounting techniques, which heavily discount future costs and benefits, may not be appropriate for long-term global challenges like climate change (Beckerman et al., 2007). The review suggests that a longer time horizon and a lower discount rate are necessary to capture the ethical dimension of intergenerational equity. Politically, the choice of discount rate reflects societal preferences and values. Different stakeholders may have contradictory views based on their interests, priorities, and time horizons. Higher discount rates may align with short-term political agendas, focussed on quick visible benefits. On the other hand, people can prefer a lower discount rate if they prioritize sustainable, future-oriented policies and proactive risk reduction.

To support this discussion point, an extra analysis was performed. In Table 6.2 the results of the analyses is shown for a discount rate of 2 percent. The main takeaway from these results is that the adaptive strategies perform much less than they initially did, when compared to the static strategies. Strategy 2, which can be seen as the robust, worse case scenario strategy, performs by far the best with a NPV of 58M€. A low discount rate assigns greater weight to future costs and benefits. In this scenario, the value of future benefits resulting from expensive investments remains relatively high compared to the immediate costs.

Although the discount rate and the associated social, ethical and political elements are out of scope for this research, it is important to acknowledge that it has a great impact on the preference for adaptive or static strategies.

Table 6.2: Impact of the discount rate on the performance of the stratgies. The benefits are much higher for t

		Original: Discount rate 4%				New: Discount rate 2%			
Strategy		NPV [M€]	Red. Risk [M€]	Investm. [M€]	Relative Diff.[%]	NPV [M€]	Red. Risk [M€]	Investm. [M€]	Relative Diff. [%]
0	Do nothing	-16.69	n.a	n.a	n.a	-52.47	n.a	n.a	n.a
1	Static SSP2-4.5	10.00	16.41	6.41	Base	46.81	54.19	7.38	Base
2	Static SSP5-8.5	9.66	16.99	7.33		**58.29**	65.84	7.54	
3	Adaptive Strategy SSP2-4.5	10.37	16.36	5.99	+7%	45.96	53.97	8.01	-13%
4	Adaptive Strategy SSP5-8.5	10.60	16.48	5.89		45.98	53.99	8.01	
5	Adaptive Strategy with flex. SSP2-4.5	9.77	16.51	6.74	-2%	45.20	53.43	8.24	-14/%
6	Adaptive Strategy with flex. SSP5-8.5	9.72	16.48	6.76		45.63	53.99	8.36	
7	Dry floodproofing & Levee	**12.85**	16.41	3.56	+31%	45.04	52.90	7.86	-14%

6.3.3. Probabilistic Evaluation

In the current two-step adaptive strategies, the time frames of the first and second time step were set. Meaning, they were not flexible or varying per MC-simulation. Furthermore, it was determined that the moment for the second measure was reached when the minimal required safety level was no longer met. In this process, a few assumptions were made to limit the range of possible scenarios. If this had not been done, the amount of variants would increase exponentially. In reality, for example, a decision maker could change the time step of the first measure, and could change the trigger value for the second measure to be implemented. For economic reasons, it might be better to set a higher trigger value (higher safety level). A more probabilistic approach could result in a more cost optimized strategy than that was found with the method applied in this framework. However, this approach would require a significant increase in computational power and may not be feasible for all projects, especially if a MC-analysis is performed for every possible combination that was found. However, in the light of the scope of this thesis, this limitation is not considered to be important. Flexibility is taken into the economic appraisal of the strategy, which was the objective of this research. When an economic optimization would the objective, a more probabilistic approach would be relevant to consider.

6.3.4. Limitations

The created framework has some limitations in both incorporating other strengths of adaptive pathways, but also testing some connected challenges.

In Chapter 3, it was discussed that the level of adaptability concerned two aspects, being the envisioned function lifetime and the lead time of the measure. In the research, the lead time is not taken in to consideration. It was assumed that the measure was ready instantly. This is a simplification, but as only measures with the same lead time are considered, the results are not impacted. When, for example, the decision maker has the choice between dry flood proofing and a seawall, the lead time plays an important role and should therefore be included. The difference in lead time for different measures is one of the challenges of adaptive pathway planning. The framework is not yet able to correctly included measures with different lead times.

Another strength of the adaptive pathway planning method is that, because long term strategies are created, lock-in can be prevented. Preventing lock-ins means avoiding situations where decisions or investments in flood risk management become rigid and irreversible, limiting future options for adaptation (Haasnoot et al., 2013). For the conceptual case study, not potential lock-in were identified. A more complex case study and more complex strategies would enable the inclusion of lock-ins and therefore quantifying the value of adaptive pathway planning.

6.3.5. Real Case Study

The developed framework was only tested on a conceptual case study, after which a couple of sensitivity tests were performed. Despite the functioning of the framework was proven, testing it for a real case study would really validate the use of the framework. For an actual case study, more costs and benefit categories can be included. The only limiting factor is that these costs need to be quantifiable. This research only focussed on economically quantifiable costs and benefits. However, as discussed in Section 3.2, not all consequences are tangible or can be monetarily valued. There are methods to quantify this kind of consequences, however there is not yet a universal, broadly accepted method.

Therefore, it can be argued if the framework provides enough performance parameters to make a well-founded decision. Besides, it can occur, in a situation where resources are not a limiting factor, this economic appraisal is less relevant. Non-economic factors like national pride can be for example a very important driver. National pride was also one of the benefit categories for the Deltaworks (Don & Stolwijk, 2003). Finally, a real case study will entail a more complex project area than used in the study. Testing the framework on a more complex system, unknown or unexpected limitations can be found.

7 Conclusions & Recommendations

Chapter 7 concludes this study by answering the defined sub-research questions and finally answer the main research question. The chapter ends with providing recommendations for future research.

7.1. Conclusions

This section provides the answer to the four sub-questions that were formulated in Section 1.2. Finally, the answer to the main research question is discussed in Section 7.1.2

7.1.1. Research sub-questions

This section provides the answers to the sub-questions. The conclusions are drawn for every sub-research question individually.

SRQ 1. How can the traditional evaluation method be extended to enable capturing the value of adaptive pathway planning?

The traditional evaluation methods of flood risk reduction strategies have their own strengths and weaknesses. However, in order to capture the value of adaptive pathway planning, certain focus point were found that needs to be considered. These focus points include uncertainty, evaluation metrics, and the value of time.

Uncertainty plays a crucial role in the performance of flood risk reduction strategies, and it is important to acknowledge and address these uncertainties in the evaluation process. Besides, it is the main motivation behind the application of adaptive planning. This can be achieved through scenario-based approaches or sampling methods, which allow for a comprehensive assessment of the strategy's effectiveness under uncertain conditions. The choice of evaluation metrics is another key aspect. By utilizing a range of metrics, decision-makers gain a more transparent understanding of the advantages and disadvantages of different strategies. This broader perspective facilitates informed decision-making and enables a more comprehensive evaluation of the strategy's performance.The value of time is also essential in the context of adaptive pathway planning. Adaptive strategies are designed to respond to future developments and incorporate decision moments throughout the project horizon. These decision moments provide opportunities for reassessment and reevaluation, based on the newest information.

In the development of a new framework to capture the value of adaptive pathways, these focus points of uncertainty, evaluation metrics, and the value of time were given special consideration. By incorporating these elements into the evaluation process, decision-makers can better assess the effectiveness and suitability of flood risk reduction strategies that embrace adaptive pathway planning.

2. In adaptive planning, what variables will experience a reduced uncertainty that can benefit the outcome?

The evaluation of stochastic variables aimed to assess whether their uncertainty would decrease over time. However, no scientific basis was found to expect a reduction in the uncertainty range of future sea level rise (SLR) projections. While initial advancements led to decreased uncertainty ranges, this trend has reversed since 2007, making the prediction of SLR evolution challenging.

Nevertheless, the next two decades are considered critical for gaining more clarity on potential scenarios. In this research, it was therefore assumed that the absolute uncertainty of SLR remains stable over time.

Regarding the economic growth rate and its impact on coastal area development benefits, site-specific factors prevented drawing a general conclusion about uncertainty reduction over time. Similarly, variables such as damage-related costs, influenced by economic growth, extreme water levels, and SLR, did not show evidence of decreasing uncertainty as time passes.

Other variables, including inflation, discount rate, and the cost of measures, also exhibited no indications of reduced uncertainty over time. These variables are expected to remain subject to uncertainty regardless of the time that passes. Therefore, for the framework, only SLR was assumed to potentially benefit from the value of time, while the other variables are considered to maintain their uncertain nature.

SRQ3. How could a framework be formulated to evaluate static and adaptive flood risk reduction strategies?

The framework effectively addressed uncertainty, evaluation metrics, and the value of time in evaluating adaptive pathway planning strategies. To account for uncertainty, a Monte Carlo analysis with a set of distributions was utilized. The method for modelling sea level rise scenarios demonstrated robust behaviour, and the probabilities associated with SLR scenarios can be easily adjusted. Furthermore, different results were found than when the strategies were tested for a deterministic future confirmed the importance. Additional metrics, including the equivalent annual cost (EAC), were included alongside NPV and BCR to enable a comprehensive evaluation. However, the probability of loss (PoL) and coefficient of variation (CV) did not provide meaningful insights in this study, although they were retained for potential future use. The value of time was confirmed, as strategies allowing for adaptation based on observed sea level rise performed approximately 6% better. This method can become even more valuable when significant variations in actions are based on experienced SLR.

In conclusion, the developed framework successfully accounted for uncertainty, employed relevant evaluation metrics, and demonstrated the value of time in assessing adaptive strategies.

4. What variables impact the robustness of the framework?

The sensitivity tests conducted on the framework focused on four key variables: the minimal required safety level, the value of time, the probabilities of the SLR scenarios, and the growth rate. The results showed that the minimal required safety level had the most significant impact on the outcomes and the suitability of measures. It is crucial to perform detailed calculations to accurately determine this level. In contrast, altering the probabilities of the SLR scenarios had minimal effects on the outcomes due to the discounting of future cash flows. The framework appeared to be relatively robust in handling variations in these probabilities. The same holds for the higher growth-rate.

However, it is important to acknowledge that the sensitivity tests performed in this study were not exhaustive. There may be additional variables that can influence the robustness of the framework, and further analysis is necessary to identify and evaluate these variables comprehensively.

7.1.2. Main research question

The research question of this thesis was formulated as follows:

> ***How can flexibility be integrated in the economic appraisal of adaptive pathway planning with uncertain future flood risk conditions?***

The developed framework successfully is able to capture the impact of uncertainty and the value of time. Although these features did not yield a significant impact on the results, the framework provides a proper foundation for further studies. Not all strengths of adaptive pathway planning, such as preventing future lock-ins, could be quantified in this analysis. Additionally, the tested strategies were simplified and did not address challenges like varying lead times of measures that arise in adaptive planning.

In conclusion, the developed framework demonstrates the ability to incorporate some strengths of adaptive pathway methods. The study highlighted that numerous factors influence strategy performance, such as the risk profile and the discount factor. When the framework is refined and validated through real case studies, it has the potential to serve as a valuable tool for decision-making. It enables the evaluation of adaptive pathways' performance and supports the justification for either a static and robust strategy or a more flexible adaptive strategy.

7.2. Recommendations

This research focussed on developing a method to include flexibility in the economic appraisal of flood risk reduction strategies. A framework was developed in which the 'extra knowledge' which is gained due to the passing of time, was included. In this chapter, recommendations are given, to deepen and broaden the developed framework in this research.

- The conceptual case study and the formulated strategies that were formulated were not complex. To further test the functioning of the framework and subsequently to improve it, the framework should be tested on a case study with a higher level of complexity. One of the options would be including strategies with different lead times or a more advance protection system, which would involve a combination of measures.
- The scope of the study only involved coastal flooding. However, when designing a flood risk reduction strategy, a more holistic approach is preferred. As coastal protection measures can have impact on the risk of pluvial or fluvial flooding. The integration of other types of flooding will test the framework further, which can lead to identifying points for improvement.
- In the discussion, it was mentioned how the framework would function when it was tested on an actual case study. Limitations were defined, but it was also described how the framework could be extended to incorporate the missing elements. Testing the framework on an actual case study is beneficial in two ways. Firstly, as a real case is not simplified, more complexities can be expected. When applying the framework on a real case, undiscovered and unexpected limitations can come to light. This can result in opportunities to enhance the quality of the framework. Secondly, testing the framework on actual case study would validate the framework and would show the potential added value.
- In Chapter 3, the factors influencing the performance of a flood risk reduction strategy were evaluated. It was investigated how the uncertainties would develop overtime and if, and how, the variable would experience a reduced uncertainty overtime. The conclusion was to only include the rate of SLR as a variable that would benefit from reduced uncertainty over time. Other variables would either not experience reduced uncertainty, like the discount and inflation rate. Or, it was concluded that the reduced uncertainty could not be described on a general level as they were depended on local conditions. However, as the working of the method was confirmed, it is interesting to evaluate its added value for more situations. The projected socio-economic development of flood prone areas is a great driver of the increased flood risk. However, these projections can include uncertainty, due to reasons like uncertainty in the developments plans for the area. It is recommended to include a scenario in which economic development of the area is included as an uncertainty, which reduces overtime. This can be expressed in the value of land €$/m^2$ and the socio-economic growth rate, or in both.

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A
Sea Level Rise Projections

A.1. Sea Level Rise Scenarios

In the late 2000s, researchers started to look how the world could change until 2100. The representative concentration pathway (RCP) were developed to describe how the different levels of greenhouse gasses would result in different radiative forcing. The values 2.6, 4.5,6.5,8.5 refer to the amount of watts per square meters. High radiative forcing means that relatively more energy is coming in than going out. For these scenarios, no socioeconomic developments are included on purpose. The way how socioeconomic factors (e.g, education, population, rate of technological development) can develop over time are described by the shared socioeconomic pathway (SSP). The SSPs describe 5 different narratives about how future society might be shaped by broad socioeconomic trends. Ranging from a sustainability focused world (SSP1) to a world dominated by rapid and unconstrained growth in economic and energy use (SSP5 (Meinshausen et al., 2020). For every SSP, it is investigated how the different RCPs could be accomplished, considering the underlying characteristics and shared policy assumptions related to that specific RCP. Not all RCP fit with every SSP. (Meinshausen et al., 2020). Figure A.1 shows the different SSP scenarios, and how the different RCP scenarios fit in.

A.2. Evolution of SLR Estimates and Ranges

A study into the trend of sea level rise projections has been conducted in order to investigate how future projections are likely to develop. A study of Garner et al. (2018) compared 70 SLR projections, published over a time span of 35 years. In figure A.2 the results of this study are presented. The interesting phenomenon that was noticed, is a reduction in the range of SLR projection from the first studies between 1983 till mid 2000s. Interestingly, from this point on this reversed and the uncertainty range grew over the years. The projections between 1983-1989 contain the greatest range from all other time periods across the 35 years. (Hoffman et al., 1983) described the scientific knowledge gap a possible explanation. The projections included many assumptions, which resulted in higher uncertainty factors, and future research should overcome these shortcomings.

The third assessment report (TAR) of the IPCC in 2001 and the studies after assumed no major contributions to SLR due to loss of founded ice from the West Atlantic Ice-sheet could be expected before 2100. From 2007 onwards, more studies showed the growing observational evidence of ice sheets loss (Rignot, Mouginot, & Scheuchl, 2011), and also accelerated the urgency of new SLR projections (20 projections between 2007 and 2013). In figure A.3, the projections from every timespan between the publications the IPCC reports. This figure visualizes the development of the projections even more clearly.

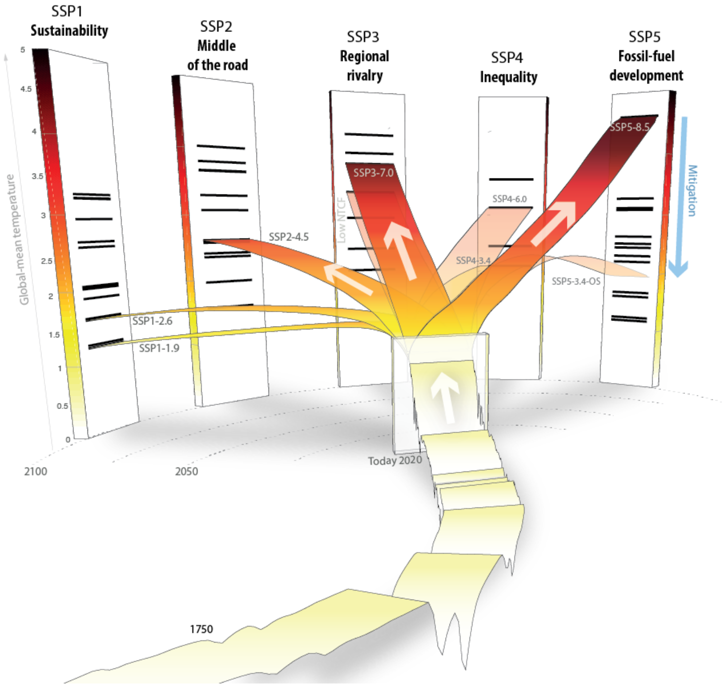


Figure A.1: Explainer of the difference between shared socioeconomic pathway (SSP) and representative concentration pathway (RCP) scenarios (Meinshausen et al., 2020)

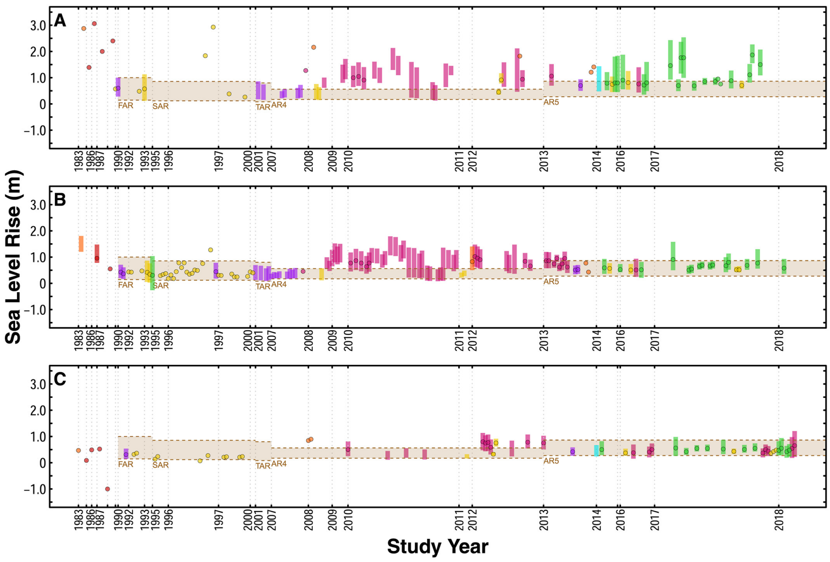


Figure A.2: Overview of the evolution of SLR projections from 1983 till 2018. The results are divided between high (a), medium (b) and low (c) scenarios. The bars (if possible) indicate the 5th and 95th- percentile range. The tan shaded lines represent the range of the IPCC reports.

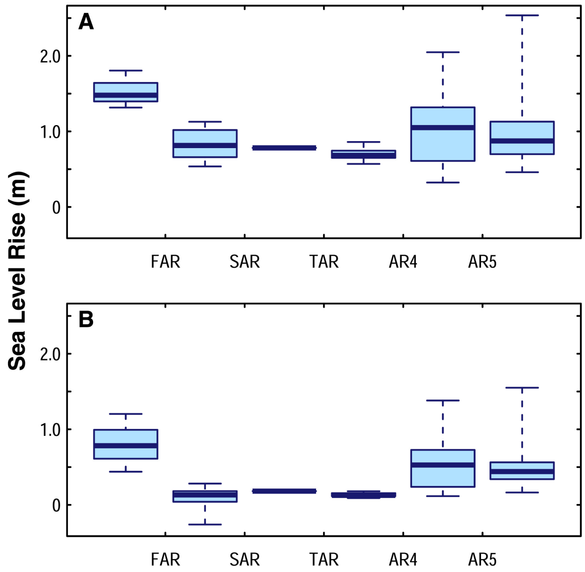


Figure A.3: Evolution of SLR projections divided by the publications of the IPPC assessments reports. The figure shows the (A) upper SLR scenario and the (B) lower SLR scenario. The box illustrates the 25th and 75th pct, the blue line defines the mean value. The whiskers present the extremes of the projections (ranging from 0 and 100th pct

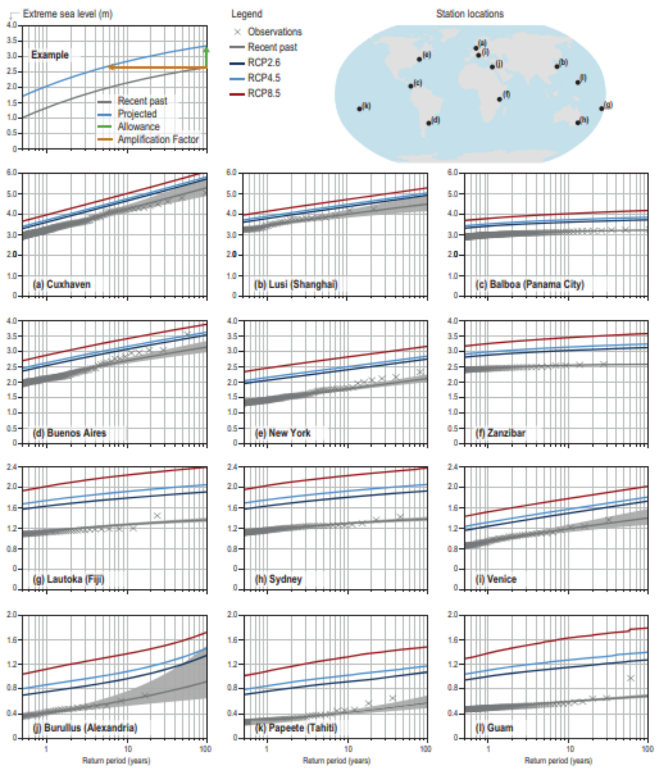
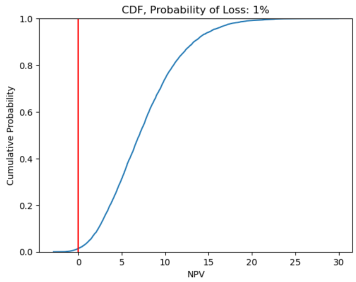
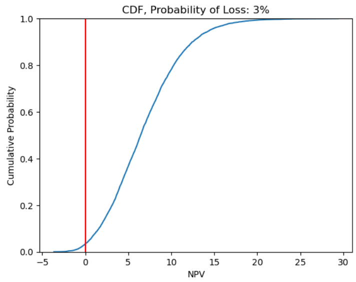


Figure A.4: change in return periods of extreme water due to SLR (Pörtner et al., 2022)

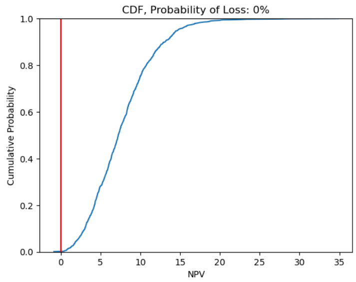
B
Results Sensitivity Tests



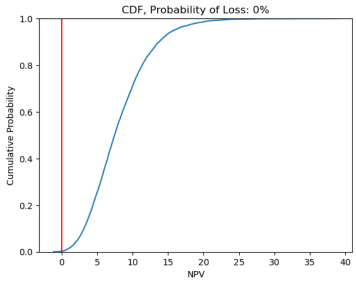
(a) CDF Strat. 1



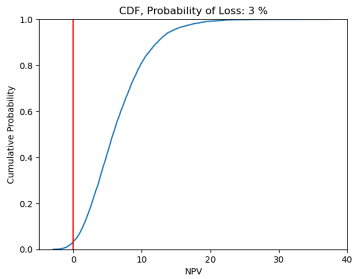
(b) CDF Strat. 2



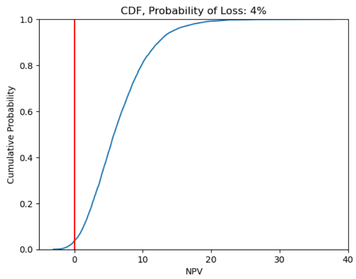
(c) CDF Strat. 3



(d) CDF Strat. 4



(e) CDF Strat. 5



(f) CDF Strat. 6

Figure B.1: Cumulative Distribution plots for the NPV for all strategies of Sensitivity Test 1

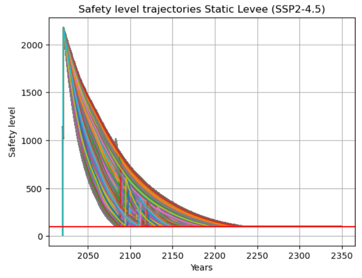
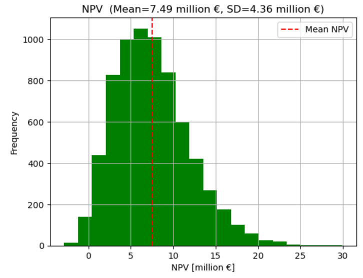
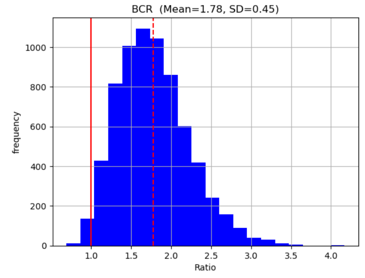
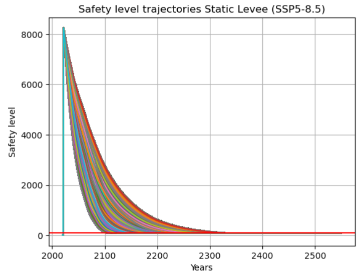
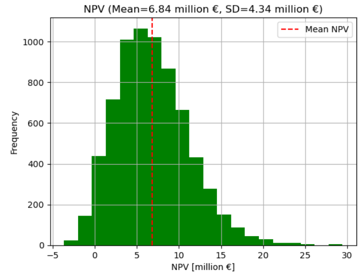
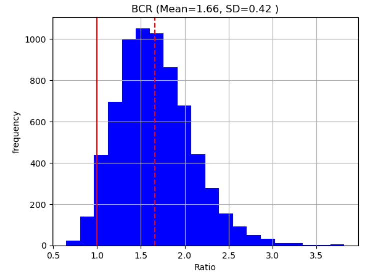
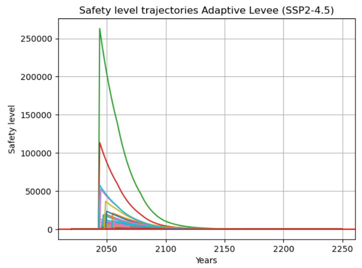
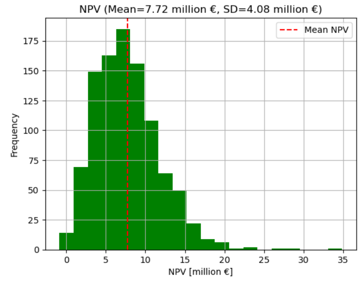
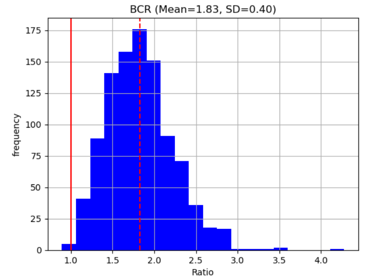
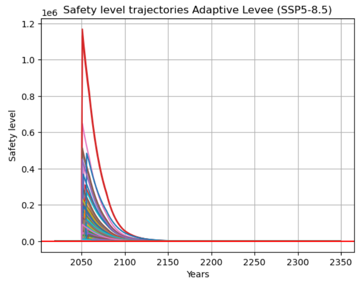
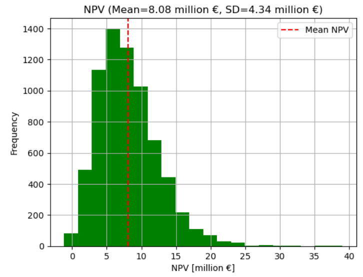
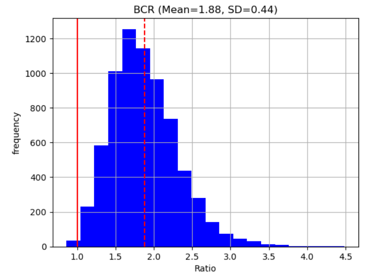
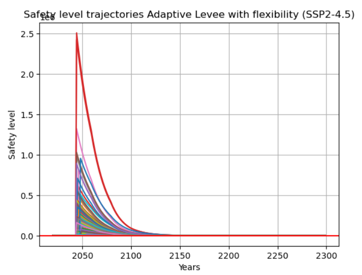
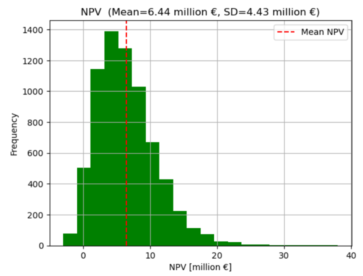
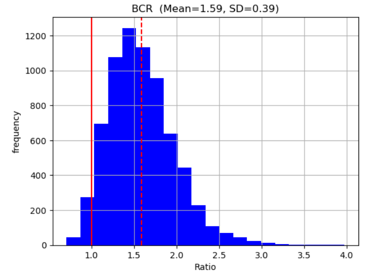
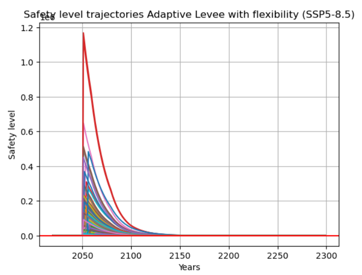
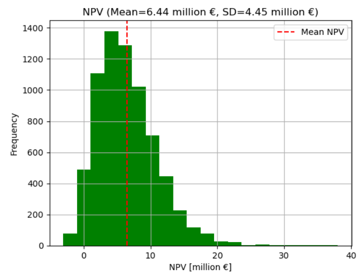
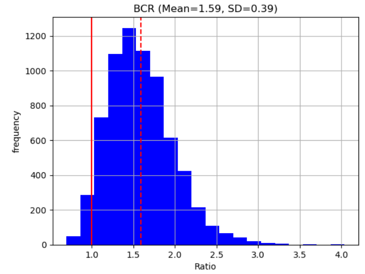
Strat.	SL-Trajectory	NPV	BCR
1			
2			
3			
4			
5			
6			

Table B.1: Results of Sensitivity Test 1: Minimal Required Safety

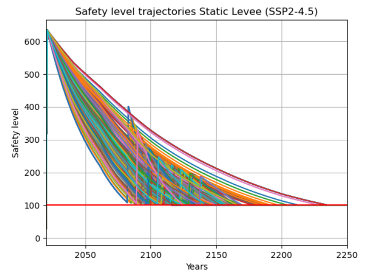
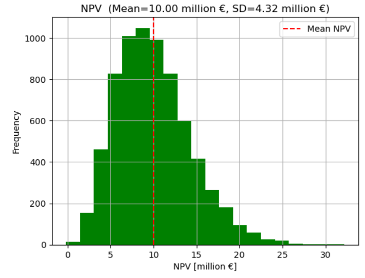
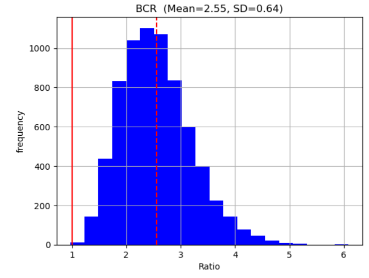
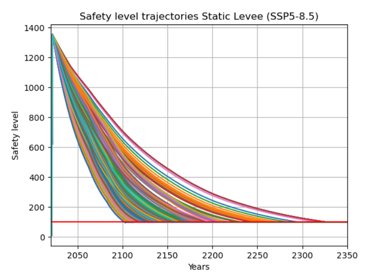
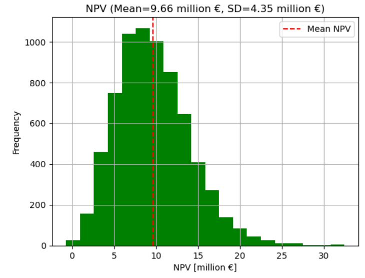
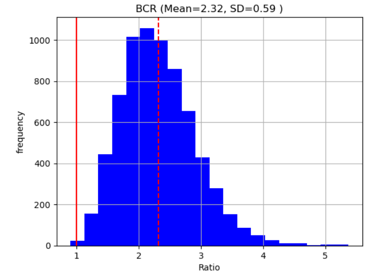
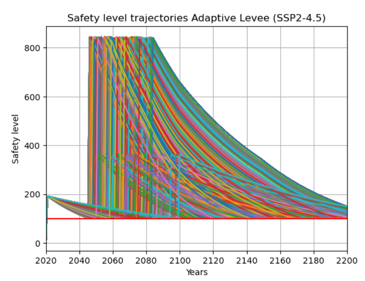
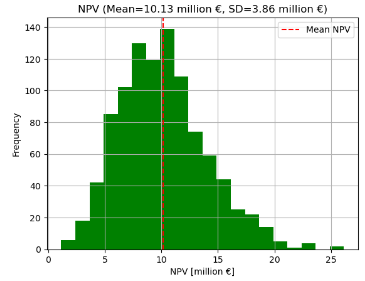
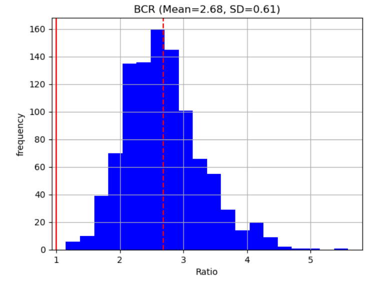
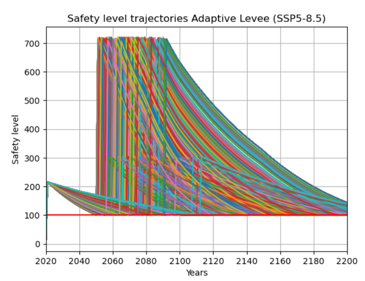
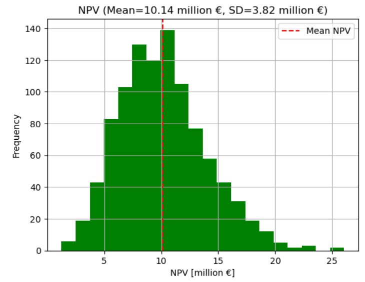
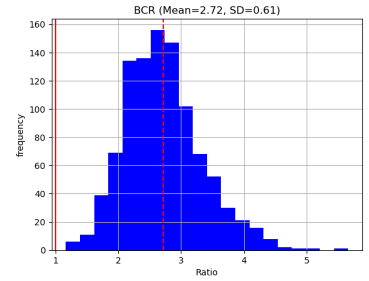
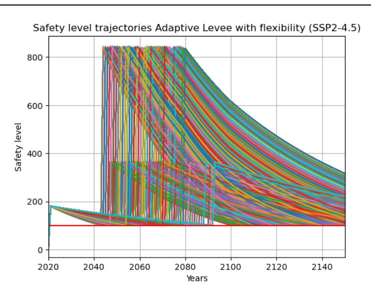
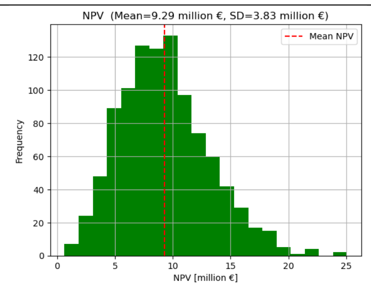
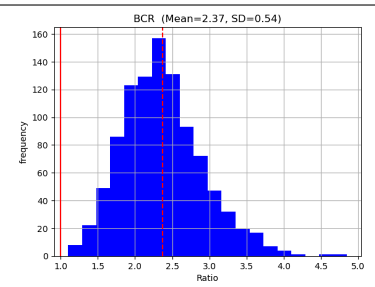
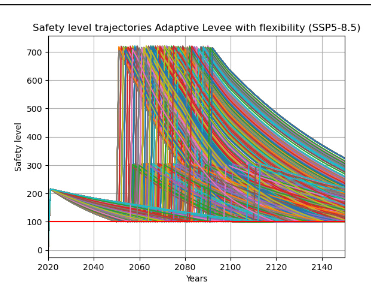
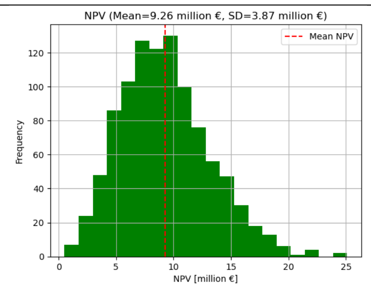
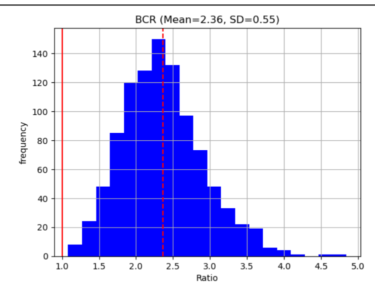
Strat.	SL-Trajectory	NPV	BCR
1			
2			
3			
4			
5			
6			

Table B.2: Results of Sensitivity Test SLR Knowledge (1/2) (plots)

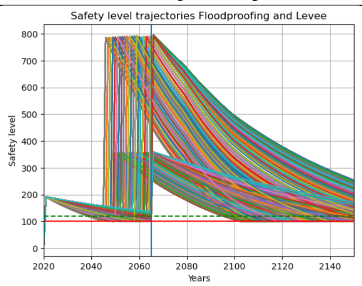
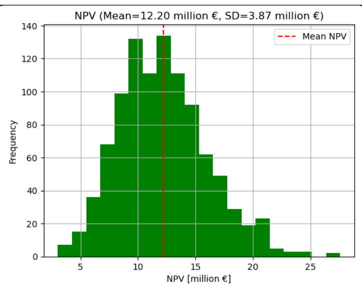
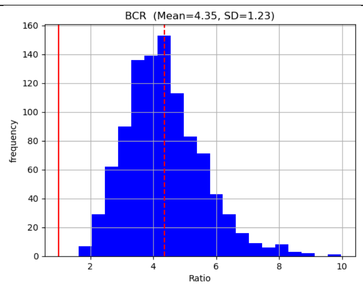
Strat.	SL-Trajectory	NPV	BCR
7			

Table B.3: Results of Sensitivity Test SLR Knowledge plots (2/2)

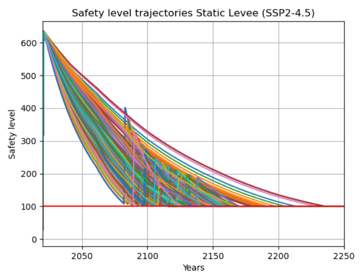
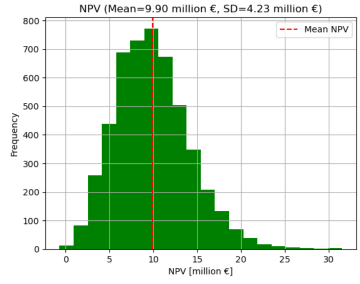
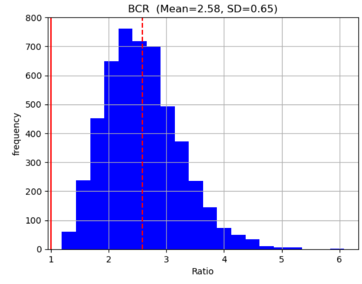
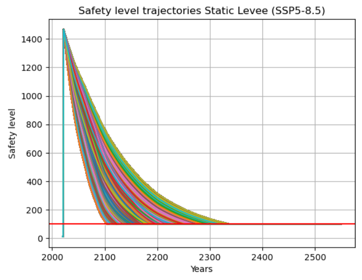
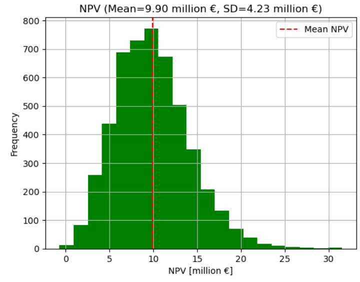
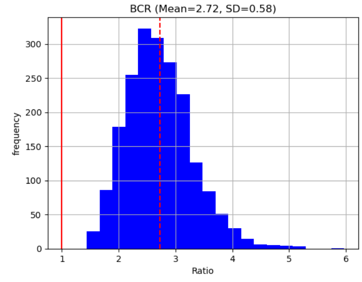
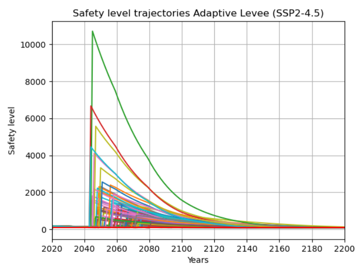
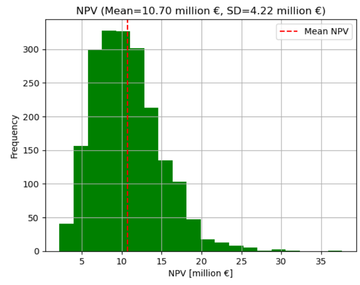
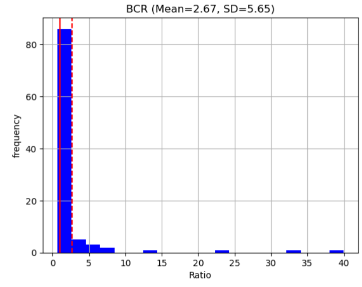
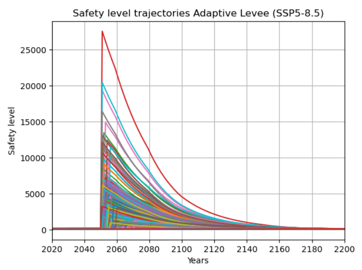
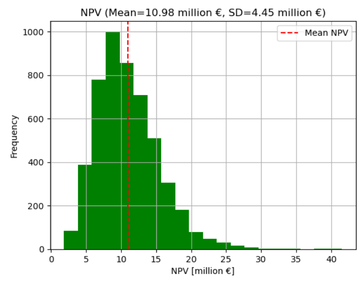
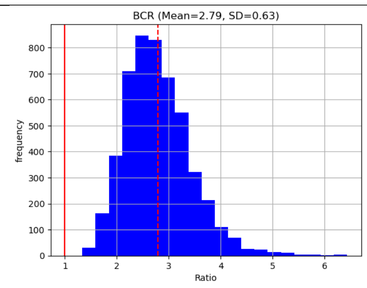
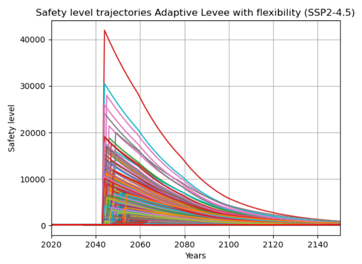
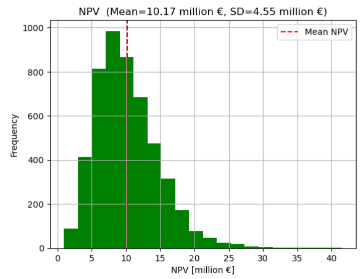
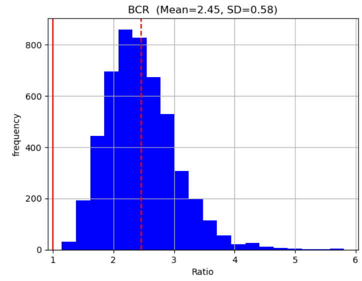
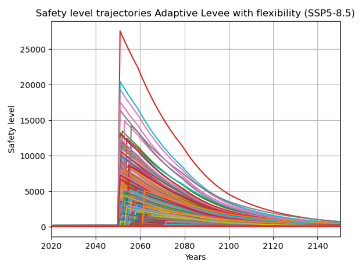
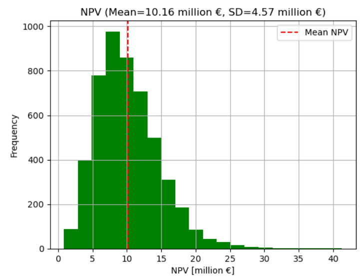
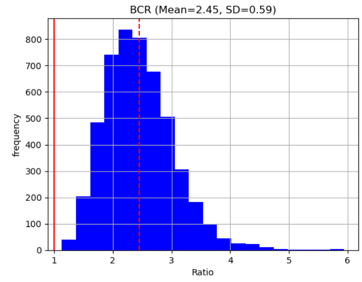
Strat.	SL-Trajectory	NPV	BCR
1			
2			
3			
4			
5			
6			

Table B.4: Results of Sensitivity Test 3: SLR-Scenario (1/2) (plots)

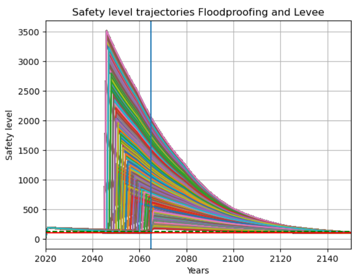
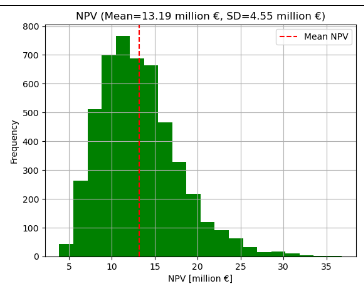
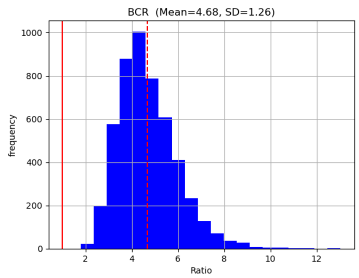
Strat.	SL-Trajectory	NPV	BCR
7			

Table B.5: Results of Sensitivity Test 3: SLR-Scenario plots (2/2)

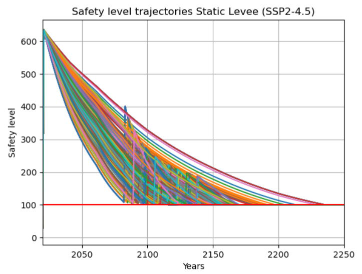
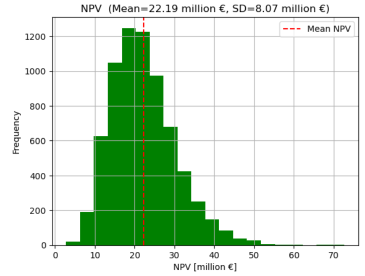
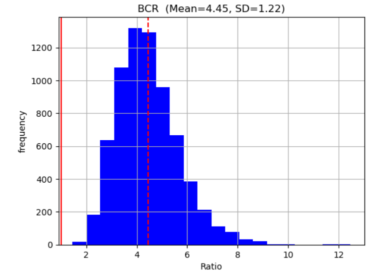
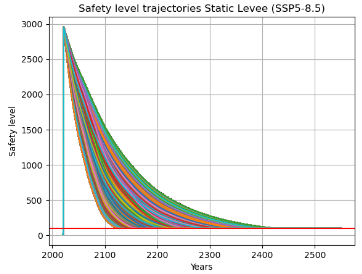
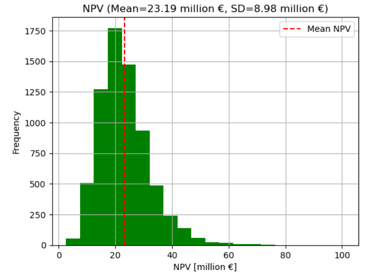
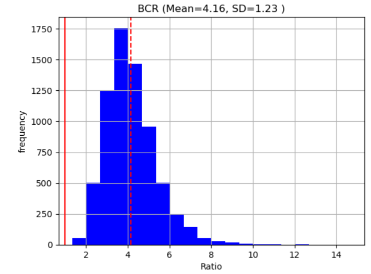
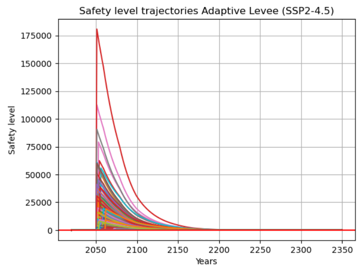
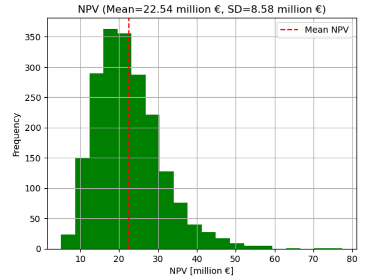
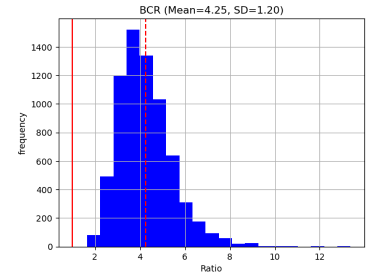
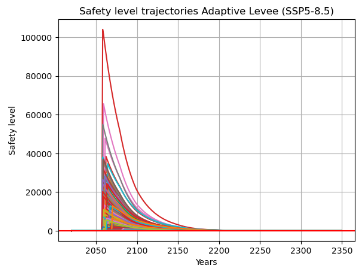
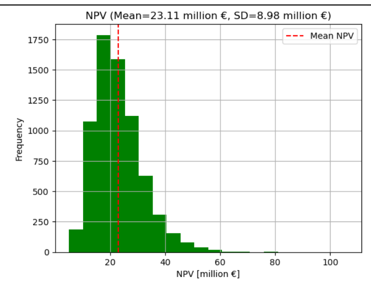
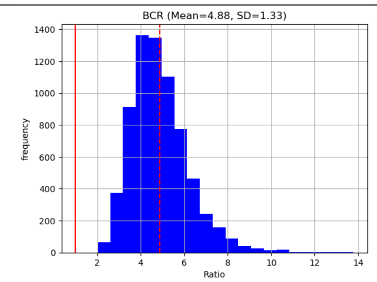
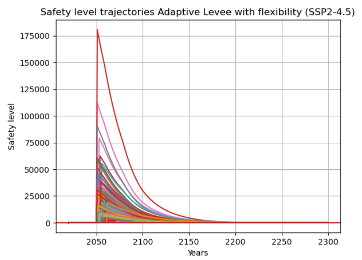
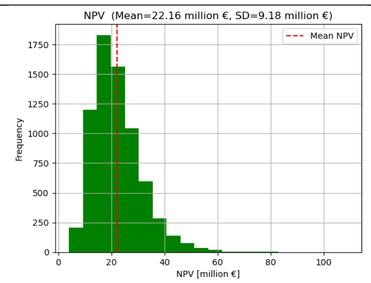
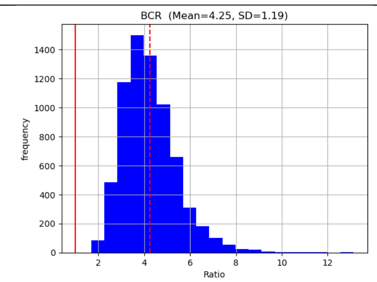
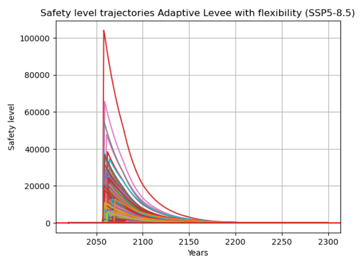
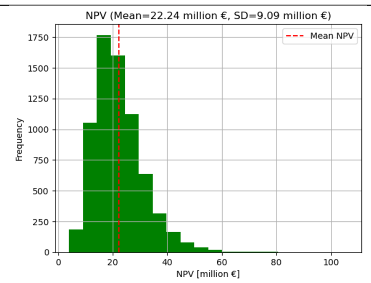
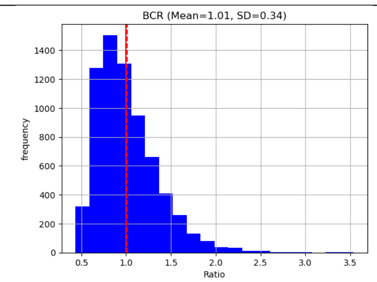
Strat.	SL-Trajectory	NPV	BCR
1			
2			
3			
4			
5			
6			

Table B.6: Results of Sensitivity Test 4: Growth-Rate (1/2) (plots)

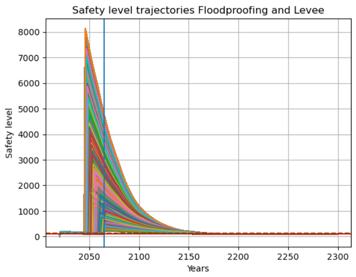
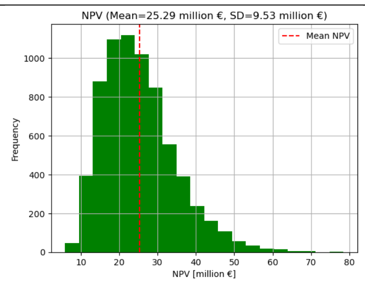
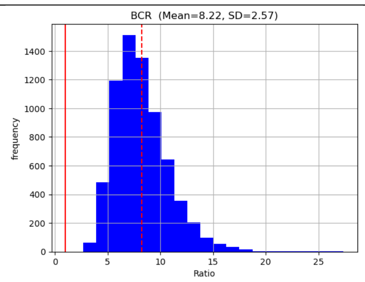
Strat.	SL-Trajectory	NPV	BCR
7			

Table B.7: Results of Sensitivity Test 4: Growth-rate plots (2/2)

C
Python Code

Below, a QR-code is provided to a GitHub file where the Python code that was developed to evaluate the strategies is uploaded. As the code would cover about 40 pages, it was decided that this would be a more practical and environmental friendly solution.

Figure C.1: QR-code to the Github file with the Python code, used for this research

And the link that can be used: https://github.com/matud1997/thesis